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Abstract

The current paper examines the driving forces of debt maturity dynamics. This is the first attempt ever made to explain debt maturity dynamics from the perspectives of variations in conventional debt maturity determinants, firm's incentive to approach the target debt maturity and the influence of the existence of extreme debt maturity users. By tracking the event time debt maturity evolution and estimating in a unified multi-period regression framework the significances of these forces, we find that debt maturity targeting effect is dominate over the other forces in driving debt maturity dynamics.

Keywords: Debt maturity; dynamics; targeting; conventional determinants; extreme cases

JEL Classification: G3

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1. Introduction

The existing empirical research on debt maturity determinants is characterized as single-period static analyses, in which the observed debt maturity is viewed as the optimal[1]. However, in a dynamic economy, there is a high probability that the observed debt maturity departs from the target due to the presence of market frictions. For instance, during tight money periods, firms may not be able to borrow as long as they want since access to credit is limited. The existing studies that aim to test the "optimal" logic and constrain themselves to static cross-sectional analyses are apparently unable to capture firms' real intention in making debt maturity decisions. In this context, it is interesting to reexamine the issue from a dynamic perspective.

The current paper studies the driving forces of debt maturity dynamics. In particular, we aim to figure out whether debt maturity dynamics are driven by changing conventional determinants or more fundamentally by firm's incentive to approach the target (optimal) debt maturity. Our empirical results show that the over-time debt maturity adjustment is explained much better by the targeting incentives than changes in previously identified debt maturity determinants. This evidence is robust even after controlling for mechanical reversion and adopting alternative definitions and measurements for debt maturity and debt maturity target.

Empirical research on debt maturity dynamics is scarce. Some first attempts are Ozkan (2000), Antoniou et al. (2006), Cai et al. (2008) and Terra (2011). Yet the results are, at best, limited. Especially, it lacks a definite test on the significance of the debt maturity targeting behaviors relative to other economic forces, for example, major changes in firm characteristics. Besides, it is not clear whether the documented targeting behavior is real or mechanical. The mechanical bias is basically originated in three ways. First, debt maturity target is often taken for granted. Target debt maturity is unobservable. The most popular method of estimating the target debt maturity (as well as the target capital structure) has been to compute the fitted value from a regression of observed debt maturity on determinants of the target. As a consequence, the existing tests of debt maturity adjustment to target are, in effect, "tests of a joint hypothesis that (1) firms adjust to target and (2) the target proxy approximates the true target relatively well"

[1] Examples of single-period specifications in debt maturity literature include Mitchell (1991), Barclay and Smith (1995), Guedes and Opler (1996), Stohs and Mauer (1996), Scherr and Hulburt (2001), Barclay, Marx and Smith (2003), Johnson (2003), Datta et al. (2005), Berger et al. (2005)), Billet et al. (2007), Saretto and Tookes (2011), and Fan et al. (2011).

(Hovakimian and Li (2011)). Second, the commonly used debt maturity measure as the proportion of long term debts with certain maturities is incapable of fully seizing the debt maturity adjustment decisions as it treats debts with maturities below and over the definition threshold as homogeneous. Imagine a situation where a firm shortens debt maturity by replacing debts due in 3 years with debts due in 1 year. The firm has an obvious intention to shorten debt maturity. But in the case that long-term debt is defined as debt maturing in more than three years, calculating the difference of long-term debt share gives rise to a misleading result indicating that no adjustment has been made. Third, the adjustment speed of debt maturity is likely to be over-estimated if "mechanical reversion" is not controlled. In their seminal papers, Shyam-Sunder and Myers (1999), Chen and Zhao (2007) and Chang and Dasgupta (2009) contend that the targeting evidence in capital structure dynamics are susceptible to mechanical reversion in which the average leverage has a natural tendency to bound off the extremes due to the fact that leverage ratio is bounded between 0 and 1. This observation is fundamental as debt maturity measured with the balance-sheet approach shares the same feature of boundary, regardless of the definition and measurement. Bearing in mind the above issues, we conduct the current research in two steps.

To begin with, we trace the event-time evolution of debt maturity measured as the weighted average maturity for a firm's total debts. Our results demonstrate that debt maturities of actual portfolios converge through time, whereas firms with initially short debt maturity continue to stay in the short debt maturity group and vice versa. This convergence pattern shows preliminary evidence of debt maturity targeting. The rationale lies in the intuition that as the observed debt maturity is not necessarily equal to the target, it is highly possible that firms sorted according to the observed debt maturity are classified into the wrong portfolios, with the two extreme portfolios misclassified to a greater extent. The targeting incentive pushes the average debt maturity towards the equilibrium, resulting in substantial convergence. For the medium and long portfolios, the targeting incentive generates two forces that cancel each other out, keeping the average debt maturity of the two moderate portfolios comparatively stable. The longest and the lowest portfolios are pushed by a single force to the centre.

Next, we examine, in a multivariate analytical framework, the driving forces of debt maturity dynamics. The forces to estimate include changes in conventional debt maturity determinants and firm's incentive to approach debt maturity target. Moreover, we decompose the targeting incentive into closing the departure from the target and keeping up with the over-time changes in target. Our results demonstrate a central role of firm's incentive to approach the target debt maturity and we find that the targeting effect accumulates through time. Depending on the empirical specification and the time frame, 9.2 to 21.9 percent of the variation in overtime debt maturity adjustment is explained by the targeting incentive. By sharp contrast, major changes in firm fundamentals explain only 3.6 to 8.7 percent of the variation. Further evidence shows that the mechanical reversion and targeting effect coexist in debt maturity adjustment. The coefficient estimates for the targeting variables are weakened after incorporating the extreme debt maturity dummies and vice versa. There is also evidence that the positive target deviation has a larger impact on debt maturity adjustment than the negative deviation. This finding is even true after controlling the extreme debt maturity cases.

For the sake of avoiding crude conclusions due to the misspecification for debt maturity target, our main analyses have employed peer firms' weighted average debt maturity as a proxy for target. In a way that the firm under observation is excluded from the calculation, this target measure is also exogenous to other explanatory variables that measure debt maturity determinants. In addition, by entering the effects of target deviation, target changes and extreme debt maturity dummies separately, we make a leap in providing neat estimates for the debt maturity targeting effect.

The remainder of the paper proceeds as follows. Section 2 reviews related literature. Section 3 discusses the data, defines the variables and presents descriptive statistics. Section 4 reports the empirical results. Section 5 concludes.

2. Related Literature

2.1. Theoretical Implications: Conventional Determinants and Optimal Debt Maturity

The finance literature has identified a set of factors that are believed to influence debt maturity determination. The most-cited are incentive provision of mitigating agency problems[2], liquidity provision of lowering financing cost, tax benefits of debt and

[2] Examples of the type of agency problems that are documented in prior research include underinvestment (e.g., Myers (1977)), asset substitution (e.g., Barnea et al. (1980) and Leland and Toft

rollover risk. Typically, researchers note that debt with short maturity acts as a discipline device for moral hazard and firms that are more prone to agency conflicts find short-term debt optimal (Myers (1977), Datta et al. (2005), and Brockman et al. (2010), among others). An alternative literature favoring the use of short-term debt has focused on the liquidity provision. For example, Taggart (1977) and Marsh (1982) posit that short-term debt has cost advantage over long-term debt as it is more liquid and therefore cheaper. Despite the benefits, short-term debt is likely to increase rollover risk, especially when maturing debt needs to be rolled over at high yields or when credit market freezes. Notably, recent research has put emphasis upon the overload of short-term debt in leading to financial distress of firms and amplifying credit market freeze during the financial crisis of 2007-2008. Researchers hold that short-term debt has compelled firms to refinance maturing debts at higher interest rates (e.g., Acharya et al. (2011)), to intensify underinvestment problems (e.g., Almeida et al. (2010), Diamond and He (2010), and Manso et al. (2010)) and to cause inefficient liquidation (e.g., He and Xiong (2012a), and He and Xiong (2012b)). Under this premise, a longer maturity of debt helps to reduce the rollover risk. Brick and Ravid (1985, 1991) show that tax advantages of debts with diverse term structures differ according to the term structure of interest rates. Long-term borrowing is preferable when the term structure of interest rates is upward sloping, and vice versa. Baker et al. (2003) and Greenwood et al. (2010) highlight firms' incentives of timing favorable financing conditions to issue short- or long-term debt in the interest of borrowing at cheaper terms. The cross-sectional implications in the above literature have been referred to in prior empirical research (Barclay and Smith (1995), Guedes and Opler (1996), Stohs and Mauer (1996), Datta et al. (2005), and Brockman et al. (2010), among others). Nevertheless, the time-series implication has not yet been emphasized and been directed tested in the literature. This literature typically poses a hypothesis such that firms manage debt maturity in response to the changes in the conventional determinants such as incentive considerations and rollover risk.

An alternative literature which provides testable hypothesis in time series suggests the existence of optimal debt maturity and transaction cost that inhibits the completion of adjustment to the target (optimal). In particular, the optimal maturity is supposed to be

(1996)), interest alignment dilemma between shareholders and managers (e.g., Rajan and Winton (1995) and Stulz (2000)), and adverse selection under opaque information environment (e.g., Flannery (1986)).

short enough to prevent managerial risk-shifting, to capture cost advantage associated with the liquidity issue but long-enough in the way to minimize loss in refinancing maturing debts. Leland and Toft (1996) were perhaps the first to formally address the optimal debt maturity issue. In a closed-form derivation, they show that longer maturity better exploits tax advantages but impedes incentive compatibility between principal and agents. As a result, firms balance the tax benefits against agency and bankruptcy costs in determining the optimal debt maturity. Ju and Ou-Yang (2006) extend the model of Leland and Toft (1996) by considering the interest rate process. They conclude that the optimal debt maturity in a stochastic interest rate environment is jointly determined with the optimal capital structure. Basically, the optimal capital structure is the result of balancing the tax shields against the bankruptcy costs of debts and the optimal debt maturity is the result of trading off the gains (i.e. the tax benefits) of dynamically adjusting the debt amount, and the losses (i.e. the transaction costs of refinancing debt) of doing so. Cheng and Milbradt (2012) analyze the optimal debt maturity of a firm based on the trade-off between incentive provision and debt run risk by creditors. They find that the optimal debt maturity rests at the interior solution that minimizes rollover risk and managers' incentives to take risk-shifting decisions. Other than focusing on the disciplinary role of short-term debt in alleviating agency incentives, He and Xiong (2012b) and Chen et al. (2013) derive the optimal debt maturity by examining the liquidity provision along with the rollover risk. Further, Diamond and He (2014) highlight the debt overhang effect on investment. They infer that the optimal maturity structure exists where long-term debt overhang in good times and short-term debt overhang in bad times are traded off. Most convincingly, in two anonymous surveys of Graham and Harvey (2001) and Bancel and Mittoo (2004)), firms do admit to engage in the activities of rebalancing the mix of debts with short and long maturities.

2.2. Empirical Evidence: The Identification of Targeting Effect

The optimal debt maturity literature implies that firms endeavor to rebalance their debt maturities when the gains of adjustment exceed the costs. Conversely, if the gains are not sufficient to offset the costs, firms rebalance debt maturity incompletely. Empirical research to test this hypothesis is however scarce. Some first attempts are Ozkan (2000), Antoniou et al. (2006), Cai et al. (2008) and Terra (2011), which find evidence and that firms in a variety of countries pursue target (optimal) debt maturities. The stylized specification used in these studies is the standard partial adjustment model[3], as specified below.

$$Y_{i,t} - Y_{i,t-1} = \alpha + \lambda\left(Y_{i,t}^{T} - Y_{i,t}\right) + \varepsilon_{i,t} \quad i = 1, \dots, n \;\; t = 1, \dots, T \qquad (1)$$

where $Y_{i,t}^{T}$ denotes the optimal (target) debt maturity for firm i at time t and λ denotes the speed of adjustment towards the target. In a frictionless world, λ is supposed to be 1, which means that the firm fully adjusts its debt maturity to the target in each period. However, in the presence of transaction cost, the firm may be reluctant to do so as the adjustment may cost too much. In this case, λ would be less than 1. The closer λ is to 1, the lower the transaction cost, and the faster the speed of adjustment.

Ozkan (2000) and Antoniou et al. (2006) show that firms in three European countries (France, Germany and the UK) adjust debt maturity quite rapidly towards the target. Analogous evidence is reported for Chinese firms by Cai et al. (2008) and for firms in Latin America by Terra (2011). Despite the efforts, the evidence found in these studies is likely to be biased according to a recent paper of Hovakimian and Li (2011) that search for reliable tests for the target adjustment hypothesis. The most common bias lies in the estimation of the optimal due to the fact that the target is unobservable and a proxy has to be used. For example, Hovakimian and Li (2011) contend that earlier tests of capital structure dynamics that fit the target from a regression of observed leverage on well-known determinants are, in effect, "tests of a joint hypothesis that (1) firms adjust to target leverage and (2) the target proxy approximates the true target relatively well". In particular, Hovakimian and Li (2011) show that the fitted target proxies in a wide range of empirical specifications are biased. Consequently, tests of this type cannot distinguish between the validation of the target proxies and the capital structure targeting evidence. The same is true for debt maturity as target debt maturity in prior studies is either implicitly imposed by running the integrated partial adjustment model or predicted from regressions of observed debt maturity on a set of firm characteristics which are believed to well proxy for the determinants of the target debt maturity. And although

[3] A growing empirical literature investigates the dynamics in firms' financing structures and the role of optimal capital structure, e.g., Jalilvand and Harris (1984), Fisher et al., (1989), Shyam-Sunder and Myers (1999), Hovakimian et al. (2001), Fama and French (2002), Leary and Roberts (2005), Flannery and Rangan (2006), Kayhan and Titman (2007), Strebulaev (2007), and Hovakimian et al. (2011).

Hovakimian and Li (2011) show that the bias can be mitigated by taking into account certain specifications, identifying the "real" target remains empirically challenging.

An alternative specification is the past average financial structure of a firm as suggested by Chen (2010). This specification works well in capturing firm-level idiosyncratic volatility, but is less reliable in short time series. Chen (2010) himself, admits that average past leverage performs poorly as a proxy for the target leverage in the first several years.

A line of studies underline the industry effect, among which the peer effect are instructive to our research. Welch (2004), Frank and Goyal (2009) and Fama and French (2012) show that industry average acts as a reliable proxy for target financial structure. Although intuitive, they do not give formal explanations. A recent paper of Leary and Roberts (2014) emphasizes the peer effect in the determination of corporate financing policies. Importantly, they elaborate that the peer effect arises from a learning motive. Firms are actually unsure of how to decide target financing structure in contrast to what the theories suggest due to the complications to estimate the relative costs and benefits of financing decisions. As a result, they imitate the financial policies of their peer firms with similar characteristics and comparable business opportunities. The findings of Leary and Roberts (2014) are enlightening to our research in defining the debt maturity target for the same reason documented for capital structure.

3. Data and Variables

3.1. Data

Our sample is confined to U.S. publicly traded non-financial non-utility firms, drawn from CRSP/Compustat Merged Database. Accordingly, we exclude firms with primary Standard Industrial Classification codes 6000-6999 (Finance, Insurance and Real Estate) and 4900-4999 (Electric, Gas, and Sanitary Services). To avoid noisy findings due to the existence of non U.S. based firms, we eliminate firms listed on U.S. stock exchanges but domiciled abroad. In turn, non-US incorporated firms and American Depositary Receipt (ADR) are removed.

Two datasets are employed. The first dataset covers firms for the period 1974–2011, used to investigate the debt maturity evolution. The second dataset intercepts the period 1986-2011 to study the main forces that drive debt maturity dynamics. The intuition of focusing on the time window from 1986 for the second dataset is to incorporate the effect of public credit access whose data type in Compustat (Standard and Poor's domestic issuer rating) is not available before 1985. Note that firms' access to public credit is found of great importance in determining corporate debt policies (se e.g., Faulkender and Petersen (2006), Sufi (2009) and Fontaine and Zhao (2013)). Another purpose is to eliminate the influence of the famous structural shift in US in the early 1980s (e.g., Fama and French (2012)).

Firm-year observations with zero debt outstanding and observations with incomplete debt maturity information are discarded. Additional, we require that a firm has at least 5 consecutive debt maturity observations in order to be included into the sample. Coding errors are corrected by excluding observations where leverage values are inferior to 0 or superior to 1. Firms with debt maturity levels less than 0 are also excluded. Our final sample is comprised of 6458 firms in first dataset and 5828 firms in the second dataset.

3.2. Variables

3.2.1. Debt Maturity Structure

Prior studies on debt maturity determinants define long-term debts as the financial obligations that are to come due in more than one year (e.g., Scherr and Hulburt (2001), Antoniou et al. (2006) and Fan et al. (2011)), three years (e.g., Barclay and Smith (1995), Barclay et al. (2003), Johnson (2003), Datta et al. (2005), and Billet et al. (2007)) or five years (e.g., Ozkan (2000) and Datta et al. (2005)). Above all, this measurement has a fatal defect when examining within-firm debt maturity dynamics, as stated above. To address this concern, we construct a value weighted debt maturity structure and define debt maturity as the value weighted average life for a firm's total debts, as shown in the formula below.

$$DMAT = \sum_{i=1}^{5} \frac{Debt_i}{Tdebt} \times Duration_i + \frac{(Tdebt - \sum_{i=1}^{5} Debt_i)}{Tdebt} \times Duration_r \tag{2}$$

Where DMAT represents the value weighted average debt maturity structure of a firm, $Debt_i$ represents the amount of debts payable in year i for i≤5. *Tdebt* refers to the amount of total debt, which is calculated as the sum of total long-term debts and debts in current liabilities.

Duration of a financial asset is defined theoretically as the weighted average length of time until all payment streams generated by the asset are received. It takes into account the elasticity of the bond price to interest rate and identifies the "actual" weighted length of time needed to recover the current cost of the bond (Copeland et al. (2005)). Due to the fact that we work on balance sheet data, we have no sufficient information (e.g., payment schedules) to calculate the real durations of all the debts employed by a firm. But at least we know the duration of a debt should always be shorter than the time-to-maturity except for zero-coupon bonds. Reasonably, we follow Jun and Jen (2003) and Chen et al. (2012) to assume that the average durations of a firm's debts payable in year 1,2,3,4,5 (denoted by $Debt_1$, $Debt_2$, $Debt_3$, $Debt_4$, $Debt_5$) are 0.5, 1.5, 2.5, 3.5 and 4.5 years respectively, denoted by $Duration_i$ for i ≤5. For the rest of debts, we assign them an average duration of 10 years, denoted by $Duration_r$. This measurement is less accurate than the measure of term-to-maturity but is more efficient in describing the complete maturity picture of a firm's debt usage and is much more precise compared to the conventionally used long-term debt proportion measure. Notably, the weighted average debt maturity measure is able to capture, to a greater degree, a firm's real intention in adjusting the maturity structure of debts, while the long-term debt proportion measure may fail to do so[4].

3.2.2. Conventional Determinants

As the major research interest of this paper is to figure out the driving forces of debt maturity dynamics, we focus on firm-specific debt maturity determinants instead of market-specific ones for economic variables are known to perform poorly in panel data and would explain only a low percentage of variation. Following the work of Fontaine and Zhao (2013), we include a vector of variables as proxies for the conventional debt maturity determinants. They are firm size, asset maturity, leverage ratio, market-to-book, R&D ratio, and public credit access. We incorporate two additional variables, cumulative stock return and stock return volatility, allowing for the effect of stock pricing.

Firm size (SIZE) is measured as the percentage of NYSE firms that have the same or smaller market capitalization. Following Stohs and Mauer (1996), we calculate asset maturity (AMAT) as the weighted average remaining maturity of fixed and current assets, weighted by their shares in total assets. We calculate book leverage (LEV) as the ratio of a firm's total debt outstanding to the book value of total assets. Market-to-Book

[4] In robustness checks, we measure corporate debt maturity structure as the proportion of interest bearing financial obligations with maturities of more than one, three and five years.

(MTB) is the book value of total assets minus the book value of common equity plus the market value of common equity, all divided by book value of total assets. R&D ratio (R&D) is the ratio of a firm's R&D expenses to the book value of total assets. Public credit access (ACCESS) is a dummy variable, which takes a value of one if Standard and Poor's domestic long-term issuer rating is available and 0 otherwise. Firm's stock return (RETURN) is the cumulative log return (monthly) on the stock over the previous year(s). Stock return volatility (VOLAT) is the standard deviation of the monthly stock return over the previous year(s).

3.2.3. Target and Target Deviation

Noting that fitting target using regressions may suffer from common bias for omitting factors, neglecting the unobservable firm fixed effects, and inducing look-ahead and in sample forecast bias (e.g., Hovakimian and Li (2011), we make reference to Leary and Roberts (2014) in constructing an industry-based target for debt maturity. Specifically, we measure a firm's peers' weighted average debt maturity (denoted as $DMAT^T$) in the same industry[5], with each firm weighted by its total liabilities. The firm under observation is excluded from the calculation to mitigate endogeneity concerns. In our robustness analyses, we test alternative debt maturity proxies such as the fitted value from regressions and past debt maturity average. The difference between the firm and its peers' debt maturity represents debt maturity target deviation, denoted as DMATD.

3.3. Descriptive Statistics

This section provides descriptive statistics for our sample firms in the second dataset. Specifically, we compute the mean, median and standard deviation for the differences of debt maturity (DMAT), firm size (SIZE), asset maturity (AMAT), leverage ratio (LEV), market-to-book (MTB), R&D ratio (R&D), public credit access (ACCESS), target debt maturity ($DMAT^T$). Same statistics are calculated for accumulative stock return (RETURN), stock return volatility (VOLAT) and prior debt maturity target deviation (DMATD). Various timelines are employed, including the 1-year, 3-years and 5-year schemes. All the variables are defined in table I. To reduce the influence of extremes, we winsorize the annual samples at the 1st and 99th percentiles in the left and right tails of SIZE, AMAT, LEV, MTB, and R&D. The results are shown in Table II.

[Insert Table I about here]

[5] Industry is defined based on Fama French 48 industry classification.

[Insert Table II about here]

Several features for debt maturity are worth noting. First, the standard deviation of the differences of debt maturity suggests important cross-sectional variation in debt maturity adjustment. Furthermore, in unreported analysis, we calculate the within firm range of debt maturity. We find that for the typical firm, the range between the firm's longest and shortest debt maturity in time series is well over four years. On the whole, it appears that debt maturity fluctuates substantially over time within firms. Second, in accordance with the recent evidence concerning the downward trend in debt maturity of U.S. firms (e.g., Custódio et al. (2013), Harford et al. (2011) and Fontaine and Zhao (2013)), our results show negative debt maturity changes. Meanwhile, target debt maturity, proxied by the weighted average debt maturity of peer firms lengthens. The average firm decreases its debt maturity by 0.03 years in one year, 0.06 years in three years and 0.10 years in five years. By contrast, the target debt maturity for the average firm increases accordingly by 0.03, 0.07 and 0.09 years. Nevertheless, the debt maturity of the typical firm deviates negatively from those of its peer firms. For example, the mean (median) value of DMATD is -1.01 (-1.67) years measured as of 1 year ago. Taken together, it indicates that U.S. firms tend to take on short-term debts excessively. Third, despite the fact that similar negative values of DMATD are observed at time t-3 and t-5, the gap narrows down with time, suggesting firms' incentives to closing the deviation.

Summary statistics for changes and accumulations in key firm features show evidence of increasing stock return & volatility, shortening asset maturity, decreasing market-to-book, and increasing access to long-term public credit. The different signs of mean and median value of changes in firm size point to the importance of large firms and the prevalence of small firms during the period 1986-2011.

4. How Can We Explain the Dynamics in Debt Maturities of Firms?

4.1. Debt Maturity Evolution

To start with, we examine debt maturity evolution in the interest of exploring the underlying patterns of debt maturity dynamics. To eliminate the measurement error induced by individual level random fluctuation and to assimilate the effects of economical and institutional shocks, we refer ourselves to the portfolio analytical framework in a way similar to Lemmon et al. (2008)[6]. The procedure is as follows. Each year, we sort firms by their debt maturities and then split them into four portfolios with equal observations, i.e. the debt maturity quartiles. Firms in the highest quartile comprise the "very long" debt maturity portfolio, and those in the lowest quartile comprise the "short" portfolio. The remaining firms comprise the "medium" and "long" debt maturity quartiles. The portfolio formation year is defined as event time 0. Event time s (-s) is s years subsequent (prior) to the portfolio formation year. For a portfolio constructed in a given year, we calculate the average debt maturity for firms present in the portfolio for the subsequent 20 years. The composition of the portfolio remains constant unless a firm spontaneously perishes and exits the portfolio. For each calendar year from 1974 through 2011, we repeat the above sorting and averaging procedure, generating 38 sets of event-time averages for each portfolio. To track the debt maturity evolution, we plot the mean of the event time averages, as shown in Figure I. The solid lines depict the portfolio's average debt maturity and the surrounding dotted lines depict the conventional 95% confidence intervals, calculated as the two-standard errors of the 38 sets of event-time averages. Results for all firms and survivors are separately presented in Panel A and Panel B. Survivors are defined as firms who have more than 20 debt maturity observations. And to allow for backward testing, we next plot the average debt maturity 10 years prior and 10 years subsequent to the year of portfolio construction, as demonstrated in Panel C (for all firms) and Panel D (for survivors).

[Insert Figure I about here]

A prominent pattern of convergence unfolds: although the dispersion of debt maturity between portfolios remains after 20 years, it becomes much less evident, implying the existence of a "decaying transitory component" in debt maturity. For all firms, the difference of the average debt maturity between the "very long" and "short" portfolios narrows down from 7.19 years at time 0 to 2.53 years at time 20. For survivors, the difference narrows down from 6.98 years to 2.50 years. Panel C and Panel D demonstrate that the dispersion is greatest around the portfolio formation year, but the convergence is observed at both ends. And the speed of convergence is much higher for the years close to the portfolio formation year.

[6] Lemmon et al. (2008) study the event time leverage evolution. We differ from them in examining the event time debt maturity evolution.

Chen (2010) contends that firms with short lives are more likely to have extreme financial structures, which leads to mechanical convergence. Indeed, the convergence is relieved when firms of this type exit the portfolios, as illustrated in Panel B and Panel D for the survivors.

To address the potential mechanical convergence due to the vanishment of short-lived firms from the portfolios, we next examine the distribution (in percentage) of strict survivor firms throughout debt maturity portfolios subsequent to portfolio formation. Precisely, we require that firms present in the initial portfolio survive 20 years following the portfolio creation year. The curves represent the percentage of firms that remain in a specific debt maturity portfolio. Firms are sorted by actual debt maturity each year and then splited into four equal groups. For each portfolio that is constructed in a given year, we calculate the percentage of firms who are present in a specific portfolio for the subsequent 20 years. The portfolio composition remains strictly unchanged. For each year from 1974 to 1991, we repeat the above sorting and averaging procedure, which generates 18 sets of event-time percentages for a portfolio. The mean of the event-time percentages is computed across event time, as shown in Table II and plotted in Figure II.

[Insert Table III about here]

[Insert Figure II about here]

As can be clearly seen, there is still a strong tendency for debt maturity to converge. Firms in a specific debt maturity portfolio subsequently transfer to other portfolios, especially to its neighboring portfolios. Within a year, 13.03% of firms in the initially “short“ portfolio move to the “medium” group. 23.37% of firms in the initially “very long” debt maturity portfolio migrate to the “long” group. 20 years later, only 48.72% (38.41%) of firms in the initially “short” (“very long”) portfolios continue to employ debts with “short” (“very long”) maturities. Meanwhile, firms that remain to stay in the same portfolio account for a larger proportion in comparison with those immigrating to other portfolios, especially in initially “short” and “very long” portfolios. Analogously, it illustrates that despite the convergence, debt maturities of long debt maturity firms remain long and debt maturities of short debt maturity firms remain short.

Above all, our preliminary evidence concerning the evolution of debt maturity indicates the presence of a transitory component in debt maturity as well as a permanent one. This finding corroborates the capital structure literature in terms of the existence of a target financial structure. For example, Lemmon et al. (2008) document eminent features of convergence and persistence for leverage evolution. They associate the pattern with the firms' incentives to rebalance leverage ratios. A follow-up paper of Chen (2010) indicates that the convergence comes down to the classification by leverage ratios different from the target levels. He argues that as the observed leverage is not necessarily equal to the target leverage, there are good chances that firms sorted according to the actual leverages are classified into the wrong portfolios. The highest and the lowest leverage portfolios are misclassified to a greater extent due to the fact that they are pushed by a single force to the centre. For the medium and high leverage portfolios, the targeting incentive generates two forces that cancel each other out, keeping the average leverage comparatively stable. To the extent that the portfolios are misclassified and firms concerns about the target leverage ratios, the convergence feature becomes distinguishing.

Table IV presents whether and to which extent firms adjust their debt maturities responding to different levels of deviation from peer firms' debt maturity. The 1-year, 3-years and 5-year windows are considered. The sample is divided up into four equal groups according to the deviation from peer firms' weighted average debt maturity (our proxy for debt maturity target deviation). The mean and median (in (parentheses)) debt maturity changes are reported for each quartile. Wilcoxon signed-rank test and student's t test are performed to test the significance of firms' debt maturity changes in each target deviation quartile.

[Insert Table IV about here]

By all accounts, it appears that peer firms' debt maturity policy, is an important concern for firms to make debt maturity decisions. The results are threefold. Firstly, consistent to our previous observations concerning the excessive usage of short-term debts, debt maturity "target" deviation is found negative in three out of four target deviation quartiles. Secondly, it appears that debt maturity responds negatively to the target deviation. The further the deviation, the greater the pace of adjustment. The mean value of the one-year debt maturity changes is 0.47 years for the lowest deviation quartile and -0.86 years for the highest quartile. Thirdly, the effect accumulates as time progresses. Over a period of five years, changes in debt maturity for the lowest deviation quartile accumulate to 1.13 years. For the highest deviation quartile, the average debt maturity shortens from 0.86 to 2.11 years.

Lemmon et al. (2008) acknowledge that ranking and classifying firms according to their actual financing structure "may simply be capturing cross-sectional variation in underlying factors associated with cross-sectional variation". That is, firms in the short debt maturity portfolio may represent firms with characteristics predicting short debt maturities (e.g. small size, short asset maturity) and vice versa. To address this concern, we examine the impacts of conventional debt maturity determinants in the following section.

4.2. Conventional Determinants

Table V reports the correlation coefficients between debt maturity changes and the concurrent changes in conventional debt maturity determinants. On the whole, debt maturity lengthens with firm size, asset maturity, debt ratios, public credit access, cumulative stock return and shortens with market-to-book ratio, and R&D expenses. Stock return volatility is negatively correlated with debt maturity changes but only in the first difference. It suggests that stock volatility affects debt maturity decisions of firms merely in the short run.

[Insert Table V about here]

We then document the impacts of the above factors in a multivariate regression framework. Specifically, we regress debt maturity changes on contemporaneous changes in conventional debt maturity determinants. The empirical model to estimate is specified as

$$DMAT_{i,t} - DMAT_{i,t-s} = \alpha + \beta_1 \Delta SIZE_{i,t,t-s} + \beta_2 \Delta AMAT_{i,t,t-s} + \beta_3 \Delta LEV_{i,t,t-s} + \beta_4 \Delta MTB_{i,t,t-s} + \beta_5 \Delta R\&D_{i,t,t-s} + \beta_6 \Delta ACCESS_{i,t,t-s} + \beta_7 RETURN_{i,t,t-s} + \beta_8 VOLAT_{i,t,t-s} + \varepsilon_{i,t} \quad i = 1, \dots, n \;\; t = 1, \dots, T \tag{3}$$

DMAT is the weighted average debt maturity structure, calculated according to Equation (1). The other variables are defined in Table I. s denotes the observation period, s=1 , 3 and 5 years. The coefficients and standard errors are estimated using the procedure of Fama-Macbeth (1973) based on the time-series of the annual cross-sectional regression coefficients. Autocorrelation-robust standard errors are reported using Newey-West adjustment.

[Insert Table VI about here]

Our estimates on debt maturity determinants are in line with prior research in general terms (e.g., Barclay and Smith (1995), Stohs and Mauer (1996), Brockman et al. (2010), etc.). Yet, it shows that the conventional debt maturity determinants only play minor roles in time series. And although the explanatory power of these factors appears to increase with the time span, the effect is not yet noticeable. The classical determinants only account for 3.6/7.2/8.7 percent of the variation in debt maturity in the first/second/third difference regressions. As it shows, the explanation power of the previously identified determinants is actually quite small.

Then what are the driving forces of debt maturity dynamics? Indeed, the permanence and convergence features in debt maturity evolution imply that the over-time debt maturity variation is probably driven by firms' incentives to approach the debt maturity targets. We expand our analysis to include this force.

4.3. Firm's Incentive to Approach the Target Debt Maturity

4.3.1. The Driving forces of Debt Maturity Dynamics: Conventional Determinants or Firm's Incentive to Approach Debt Maturity Target

To take into account firms' incentive to approach target debt maturity, we consider a partial adjustment process, in which a firm strives to close the gap between its actual and target debt maturity. In a multi-period setting, the empirical specification is formulated as

$$DMAT_{i,t} - DMAT_{i,t-s} = \alpha + \lambda_1 DMATD_{i,t-s} + \varepsilon_{i,t} \quad i = 1, \ldots, n \;\; t = 1, \ldots, T \tag{4}$$

DMATD denotes debt maturity target deviation, which is the difference between the observed and the target debt maturity ($DMAT_{i,t-s} = DMAT_{i,t-s} - DMAT^T_{i,t-s}$, where $DMAT^T_{i,t-s}$ denotes the target debt maturity for firm i at time t-s, i.e. the beginning of the observation period). The adjustment speed parameter λ_1 is expected to be negative and its absolute value is expected to be less than 1, allowing that firms may not be able or willing to realize the adjustment instantly.

In an expanded version, the firm considers closing target deviation and narrowing down target changes. The empirical model is developed as below.

$$DMAT_{i,t} - DMAT_{i,t-s} = \alpha + \lambda_1 DMATD_{i,t-s} + \lambda_2 \Delta DMAT^T_{i,t,t-s} + \varepsilon_{i,t} \quad i = 1, \ldots, n \;\; t = 1, \ldots, T \tag{5}$$

Where $\Delta DMAT^{T}_{i,t,t-s}$ represents debt maturity target changes.

Further development includes changes in conventional debt maturity determinants, which yields

$$DMAT_{i,t} - DMAT_{i,t-s} = \alpha + \beta_1 \Delta SIZE_{i,t,t-s} + \beta_2 \Delta AMAT_{i,t,t-s} + \beta_3 \Delta LEV_{i,t,t-s} + \beta_4 \Delta MTB_{i,t,t-s} + \beta_5 \Delta R\&D_{i,t,t-s} + \beta_6 \Delta ACCESS_{i,t,t-s} + \beta_7 RETURN_{i,t,t-s} + \beta_8 VOLAT_{i,t,t-s} + \lambda_1 DMATD_{i,t-s} + \lambda_2 \Delta DMAT^{T}_{i,t,t-s} + \varepsilon_{i,t} \quad i = 1, \dots, n \;\; t = 1, \dots, T \tag{6}$$

The regression results of the specifications (4), (5) and (6) are reported in Table VII, along with the sensitivity analysis for the magnitude effect, i.e., the variability of real debt maturity changes in response to one standard deviation increase in the right-hand side variables.

[Insert Table VII about here]

Probably the most interesting finding is that a large percentage of the variation in debt maturity changes is explained by the single variable of prior debt maturity deviation ($DMATD_{t-s}$). The coefficient of determination for specification (4) ranges from 0.090 in the one-year time span to 0.212 in the five-year time span. The inclusion of conventional determinants of debt maturity only increases the explained variation by 3.8, 7.5 and 8.5 percent in the one-, three- and five-year time spans respectively. The explanatory power of the model increases negligibly when including target changes. This finding is actually not surprising. As using peer firms' average debt maturity as a target proxy suppresses the component of target changes led by firm-level idiosyncratic volatility and thus is likely to weaken the estimates for the effect of target changes.

Furthermore, in support of our hypothesis concerning debt maturity targeting, we find significantly negative coefficients for $DMATD_{t-s}$. Depending on the specifications, a one standard deviation increases in the target deviation variable results in a curtailment of debt maturity by 0.55-0.58 in one year, 1.06-1.12 in three years and 1.32-1.41 in five years.

Additionally, our results favor the hypothesis on the effect of target changes. The coefficient of $\Delta DMAT^{T}$ is positive and significant in both statistical and economical terms. A one standard deviation increase in peer firms' debt maturity changes is associated with the lengthening of debt maturity for 0.07/0.23/0.29 years in the one-/three-/five-year time frame.

Another feature is worth noting. The economic significance of most right-hand side variables increases with the observation interval. some doubled and others even tripled. This may be due to the fact that the effects of these variables persist in time and temporary fluctuations in these variables play smaller parts in firms' financial decisions comparing with long-lasting fluctuations. Two exceptions are $\Delta MTB_{i,t,t-s}$ and $RETURN_{i,t,t-s}$. A one standard deviation increase in cumulative stock return lengthens debt maturity by 0.13 years in one year but by only 0.06 years in five years. A short explanation is that the effects of these two variables reverse in time, probably due to the market timing practice. As this subject is beyond the scope of this paper, we leave it for future research.

4.3.2. Firm's Incentive to Approach Debt Maturity Target and the Role of Extreme Cases

On the whole, the above regression results indicate a nontrivial role of debt maturity target, in both short and long run. Nonetheless, recent papers address the issue of mechanical reversion (e.g., Shyam-Sunder and Myers (1999), Chen and Zhao (2007), Chang and Dasgupta (2009), according to which financial structure has a natural tendency to revert back to the mean due to the boundary feature. In other words, one cannot distinguish purely mechanical from intentional targeting without controlling the influence of the extreme cases which, by definition, are close to the bound. On the other hand, there are reasons to believe that extreme debt maturity cases are potentially overlapped with the off-the-optimum observations. To the extent that the off-the-optimum observations are prevalent in the extremes, factors of optimal debt maturity structure may rapidly lose their explanation power. Related implications can be drawn from the seminar work of Fontaine and Zhao (2013) which find attenuation effects of conventional determinants in the tails of the debt maturity distribution. Studying the dynamic pattern of previously extreme debt maturity users would therefore be of interest by answering the question of whether short (long) debt maturity users continue to employ debts with short (long) maturities after ruling out the targeting incentive.

The common practice to address the mechanical mean reversion in the literature is to eliminate the extreme cases or to incorporate corresponding dummies for the extreme cases. Although instructive, the former may induce selection bias and the latter may induce collinearity. We adopt the two devils for robustness. Specifically, we refer extreme cases to firms present at the 10th and 90th percentiles in the annual debt maturity distribution. And we implement three empirical specifications. The first specification excludes the extreme cases and re-estimates Model (6). The second specification includes extreme debt maturity dummies while excludes debt maturity target deviation and target changes, as specified in Model (7). The purpose is to examine how and to which extent debt maturities of previously extreme debt maturity users evolve in time without taking into account the targeting incentives of firms. The last specification (shown in Model (8)) considers both extreme dummies and targeting variables, on the grounds that extreme debt maturity cases are possibly overlapped with the off-the-optimum observations[7]. Results are reported in Table VIII.

$$DMAT_{i,t} - DMAT_{i,t-s} = \alpha + \beta_1 \Delta SIZE_{i,t,t-s} + \beta_2 \Delta AMAT_{i,t,t-s} + \beta_3 \Delta LEV_{i,t,t-s} + \beta_4 \Delta MTB_{i,t,t-s} + \beta_5 \Delta R\&D_{i,t,t-s} + \beta_6 \Delta ACCESS_{i,t,t-s} + \beta_7 RETURN_{i,t,t-s} + \beta_8 VOLAT_{i,t,t-s} + \gamma_1 SHORT_{i,t-s} + \gamma_2 LONG_{i,t-s} + \varepsilon_{i,t} \qquad i = 1, \dots, n \;\; t = 1, \dots, T \tag{7}$$

$$DMAT_{i,t} - DMAT_{i,t-s} = \alpha + \beta_1 \Delta SIZE_{i,t,t-s} + \beta_2 \Delta AMAT_{i,t,t-s} + \beta_3 \Delta LEV_{i,t,t-s} + \beta_4 \Delta MTB_{i,t,t-s} + \beta_5 \Delta R\&D_{i,t,t-s} + \beta_6 \Delta ACCESS_{i,t,t-s} + \beta_7 RETURN_{i,t,t-s} + \beta_8 VOLAT_{i,t,t-s} + \lambda_1 DMATD_{i,t-s} + \lambda_2 \Delta DMAT^{T}_{i,t,t-s} + \gamma_1 SHORT_{i,t-s} + \gamma_2 LONG_{i,t-s} + \varepsilon_{i,t} \qquad i = 1, \dots, n \;\; t = 1, \dots, T \tag{8}$$

Here SHORT is a dummy variable for extremely short debt maturity users, which takes a value of 1 if debt maturity of a firm is at the 10th debt maturity percentile. LONG is a dummy variable for extremely long debt maturity users, i.e. firms present at the 90th debt maturity percentile.

[Insert Table VIII about here]

In line with the mechanical reversion proposition, the magnitude of the estimates for DMATD $_{t-s}$ is weakened after excluding the extreme debt maturity users from the sample and incorporating the extreme debt maturity dummies. The estimates for Model (7) indicates that firms whose debt maturities are exceedingly long in a prior year incline themselves towards short-term debts, while firms with exceedingly short prior debt maturities incline themselves towards long-term debts. Debt maturity adjustment for the remaining firms shows no clear patterns. The estimates for the estreme debt maturity dummies are mitigated after including the variables that proxy for firms' debt maturity targeting incentives ($DMATD_{i,t-s}$ and $\Delta DMAT^{T}_{i,t,t-s}$). In the one-year time frame,

[7] In the unreported analysis, we check frequency distribution across the debt maturity structure and the debt maturity target deviation quartiles. The analysis is conducted for all and survivor firms separately. The results confirm in a statistical term the overlap between the extreme debt maturity cases and the off-the-optimum observations.

the magnitude of estimates for the variable LONG decreases from 1.41 (Model (7)) to 0.52 (Model (8)), nearly dropped by a third although not totally eliminated. In contrast, controlling the targeting incentive changes the signs of the short debt maturity dummy. Above all, our results suggest that short debt maturity extremes are more likely to be temporarily off-the-optimum. Clear off the targeting incentive, firms of this type continue to rely exclusively on short-maturity debts.

4.3.3. Firm's Incentive to Approach Debt Maturity Target: Positive Deviation versus Negative Deviation

It is possible that the effects of the negative and positive target deviation differ in magnitude. To address this concern, we re-specify the model as follows.

$$DMAT_{i,t} - DMAT_{i,t-s} = \alpha + \beta_1 \Delta SIZE_{i,t,t-s} + \beta_2 \Delta AMAT_{i,t,t-s} + \beta_3 \Delta LEV_{i,t,t-s} + \beta_4 \Delta MTB_{i,t,t-s} + \beta_5 \Delta R\&D_{i,t,t-s} + \beta_6 \Delta ACCESS_{i,t,t-s} + \beta_7 RETURN_{i,t,t-s} + \beta_8 VOLAT_{i,t,t-s} + \lambda_1 DMATD_{i,t-s} + \lambda_2 \Delta DMAT^T_{i,t,t-s} + \gamma_1 SHORT_{i,t-s} + \gamma_2 LONG_{i,t-s} + \lambda_3 NEG_{i,t-s} + \lambda_4 NEG_{i,t-s} \times DMATD_{i,t-s} + \varepsilon_{i,t} \quad i = 1, \dots, n \;\; t = 1, \dots, T \tag{9}$$

where NEG is the dummy variable for negative debt maturity target deviation. $NEG \times DMATD$ is the interaction item between negative target deviation dummy and debt maturity target deviation. The parameter of interest is λ_4, which measures the effect difference between the positive and the negative target deviation. For brevity, we only report estimates for λ_1, λ_3 andλ_4(in Table IX).

[Insert Table IX about here]

Notably, the estimates for λ_4 are always positive and statistically significant, indicating the greater impact of the positive target deviation relative to the negative deviation. Specifically, a one unit increase in the positive target deviation curtails debt maturity by 0.18, 0.37 and 0.50 in one, three and five years respectively. In contrast, a one unit decrease in the negative target deviation prolongs debt maturity by only 0.12, 0.23 and 0.30 in the corresponding time frame.

4.4. Robustness

The preceding results demonstrate that after taking into account the targeting effect of approaching peer firms' debt maturity, extremely long debt maturity users have a tendency to bounce off the upper boundary, in line with the mechanical reversion argument. However, extremely short debt maturity users continue to use more short-term debts. One may argue that the opposite adjustment pattern of the two extreme debt maturity users would be due to the fact that using industry average to proxy for firm's target financial structure overlooks firm-level idiosyncratic demand for short debt maturity.

To check robustness, we estimate debt maturity target with alternative specifications. Precisely, we measure the OLS regression fitted debt maturity, the quantile regression fitted debt maturity and the past average debt maturity. For the purpose of capturing the unobservable firm fixed effects, avoiding the look-ahead bias and providing the out of sample prediction, Hovakimian and Li (2011) propose to predict the target financial structure using firms' historical panel information. Following this intuition, we estimate parameters for the regression models based on firms' complete historical panel information. Specifically, we regress observed debt maturity on a selection of factors whose effects are previously found prominent and persistent in deciding the maturity structure of corporate debts. They are firm size, leverage, asset maturity, market-to-book, R&D ratio and a set of industry dummies constructed according to 48 Fama-French industry classification. Allowing for delays in firms' financing decisions, all the explanatory variables (defined in Table I) are lagged one period. The model is specified as follows,

$$DMAT_{i,t} = \alpha_\theta + \beta_{1\theta} Size_{i,t-1} + \beta_{2\theta} Leverage_{i,t-1} + \beta_{3\theta} Asset\ Maturity_{i,t-1} +$$

$$\beta_{4\theta}\ Market - to - Book_{i,t-1} + \beta_{5\theta} R\&D_{i,t-1} + \gamma_\theta Industry_i + \varepsilon_{i,t} \quad i = 1, \dots, n \ \ t = 1, \dots, T \qquad (10)$$

The debt maturity target for firm i in year t is computed by applying the coefficient estimates to firm i's characteristics measured as of year t-1.

Enlightened by Graham and Leary (2011) and Fontaine and Zhao (2013) [8], we next employ the quantile regression approach to estimate the parameters, accounting for the non-monotonic effects of debt maturity determinants. Precisely, we regress the conditional quantiles of debt maturity on important debt maturity determinants. Below is our estimation model[9].

[8] Fontaine and Zhao (2013) address the uneven effects of debt maturity determinants across the debt maturity distribution.

[9] Due to the lack of data before 1985 for Standard and Poor's domestic issuer rating which is used to define firms' public credit access, long- and short-term public credit accesses are not incorporated into the model.

$$\left(DMAT_{i,t} \middle| X_{i,t-1}\right) = \alpha_\theta + \beta_{1\theta} Size_{i,t-1} + \beta_{2\theta} Leverage_{i,t-1} + \beta_{3\theta} Asset\ Maturity_{i,t-1} + \beta_{4\theta} Market - to - Book_{i,t-1} + \beta_{5\theta} R\&D_{i,t-1} + \gamma_{i\theta} Industry_i + \varepsilon_{i,t} \quad i = 1, \dots, n \;\; t = 1, \dots, T \tag{11}$$

The 25th, 50th, and 75th quantiles of debt maturity (DMAT) for firm i observed in year t is regressed on firm-specific characteristics observed in year t-1. The target debt maturity for the firm i in year t is computed by applying the coefficient estimates corresponding to the debt maturity quantile as of year t-1. That is, the 25th quantile regression results apply to $DMAT_{t-1}$ inferior to the 0.25 percentile, the 50th quantile regression results apply to $DMAT_{t-1}$ superior to the 0.25 percentile and inferior to the 0.75 percentile, and the 75th quantile regression results apply to $DMAT_{t-1}$ superior to the 0.75 percentile.

Lastly, we calculate the time-series average of a firm's historical debt maturities by reference to Chen (2010).

Since the OLS and quantile regression fitted target are functions of debt maturity determinants, and firm's past debt maturity contains a firm-fixed effect which is correlated with debt maturity and therefore its determinants, incorporating the target changes measuring in this way and the conventional determinants in the same regression framework is likely to induce severe endogeneity problem. So we discard changes in conventional debt maturity determinants in the model to check robustness as follows.

$$DMAT_{i,t} - DMAT_{i,t-s} = \alpha + \lambda_1 DMATD_{i,t-s} + \lambda_2 \Delta DMAT^T_{i,t,t-s} + \gamma_1 SHORT_{i,t-s} + \gamma_2 LONG_{i,t-s} + \varepsilon_{i,t} \quad i = 1, \dots, n \;\; t = 1, \tag{12}$$

$$DMAT_{i,t} - DMAT_{i,t-s} = \alpha + \lambda_1 DMATD_{i,t-s} + \lambda_2 \Delta DMAT^T_{i,t,t-s} + \gamma_1 SHORT_{i,t-s} + \gamma_2 LONG_{i,t-s} + \lambda_3 NEG_{i,t-s} + \lambda_4 NEG_{i,t-s} \times DMATD_{i,t-s} + \varepsilon_{i,t} \quad i = 1, \dots, n \;\; t = 1, \dots, T \tag{13}$$

Regression results are shown in Table X. In a way that our measure of peer firms' debt maturity discards the observed firm's debt maturity, the collinearity between debt maturity determinants and its target is greatly mitigated.

[Insert Table X about here]

Qualitatively, we find the robustness of our main findings concerning the significance of managerial debt maturity targeting behaviors. The influence of $DMATD_{i,t-s}$ (target deviation) is smallest when debt maturity target is proxied by peer firms' debt maturity target and largest when past average debt maturity is used as a proxy. The results are logical as the specification in which debt maturity target is measured using past average debt maturity is supposed to capture historical volatility of a firm to a largest extent. Analogously, this specification reports the most prominent effect of target changes (except in the one-year timeline), followed by the quantile regression. A possible explanation is that the quantile regression technique describes the relationships between debt maturity and its determinants more completely, thus the estimates from the quantile regressions fit the target better. Precedent findings in terms of the greater impact of positive target deviation are also robust.

The only divergence rests with the estimates for the short debt maturity dummy. Specifically, estimates for SHORT turn to positive in the "QR" and "Past Mean" specifications. Conversely, the estimates for the long debt maturity dummy are consistent with our preceding results in Table VIII using peer firms' weighted average debt maturity as the target proxy. The divergence could be explained by the inertia or termed as the permanence in debt maturity. To the extent that past debt maturity average and the quantile regression method captures the inertia, the permanent feature of short debt maturity which is not captured by the industry debt maturity would be otherwise absorbed.

Our unreported robustness analyses estimate debt maturity target with additional predictive variables of firm age, abnormal earnings, asset volatility and cash holdings[10]. We also turn to different debt maturity definitions: the proportion of interest bearing financial obligations with maturities of more than one, three and five years as in Barclay and Smith (1995), Johnson (2003) and Antoniou et al. (2006). The final robustness test uses alternative duration cutoffs to construct the weighted average debt maturity measure. We assume that the average durations of a firm's debts payable in year 1, 2, 3, 4, 5, 5+ are 0.3, 1.3, 2.3, 3.3, 4.3, 10 years in the first place, 0.7, 1.7, 2.7, 3.7, 4.7, 10 years in the second place and 0.5, 1.5, 2.5, 3.5, 4.5, 20 years in the last place. By and large, these analyses show no violation of our main findings.

[10] We measure firm age as the number of years and months elapsed since a firm's first CRSP listing date. Abnormal earnings is the difference of the income before extraordinary items adjusted for common stock and equivalent between year t+1 and t divided by market capitalization in calendar year t. Asset volatility is the difference between the asset volatility of a firm and the asset volatility of the industry of the firm. Asset Volatility of A Firm =Monthly Stock Return Standard Deviation during a Firm's Fiscal Year × (Market Value of Common Equity ÷ Market Value of Total Assets). Cash holdings is the ratio of a firm's cash and short-term investment to total assets.

4.5. Discussions

We show that the incentive to approach peer firms' debt maturity has a significant impact on debt maturity adjustment and the impact persists over time.

Now consider a firm suffering from short-run business downturn and having its debt maturity temporarily deviating far from the target level. If the targeting incentive holds, firm would close the deviation as far as it might yet be possible in the following periods. To test this hypothesis, we extend the precedent analysis on debt maturity evolution to study the evolution of debt maturity target deviation. Portfolios are still constructed on actual debt maturities of firms, but the evolution of target deviation is plotted (Figure III). Hence, instead of tracing the event-time average debt maturity, we trace the event-time average debt maturity target deviation which, by definition, is the residual between the observed value of debt maturity and the target value. Debt maturity target is estimated as the weighted average debt maturity of peer firms in the same industry in Panel A and Panel B, as the fitted value from the OLS regression in Panel C and Panel D, as the fitted value from the quantile regression in Panel E and Panel F and as the time-series average of a firm's historical debt maturities in Panel G and Panel H. The solid curves represent the portfolio's average debt maturity target deviation and the long-dashed curves surrounded represent the 95% confidence interval.

[Insert Figure III about here]

Corroborating the idea of Chen (2010) that debt maturity at portfolio formation time is extreme for an individual firm, we find that, regardless of the target proxy, the divergence of debt maturity target deviation is always greatest at event 0, with positive average deviation found for the "Very Long" portfolio and negative average deviation for the "Short" portfolio. As event time progresses, the cross-sectional dispersion of the target deviation becomes rapidly indistinguishable, especially between the "Very Long" and "Long" portfolios and in the specification where debt maturity target is predicted using the quantile regression method. In the specification where firm's past debt maturity average is used to proxy for target, the convergence is most overwhelming. The relative position of the portfolios is reversed in less than 5 years. Additionally, there's a hint of permanence in the negative target deviation of the "Short" portfolio in Panel A, B, C and D, suggesting that in equilibrium debt maturities of short debt maturity users tend to be shorter relative to their industry peers, even after taking into account firm-specific characteristics. Indeed, such pattern vanishes in the specifications when previous debt maturity levels are used as a proxy (see Panel E and F) or controlled to predict target debt maturity (see Panel G and H).

On the whole, the above findings indicate that active management of debts with various maturities is largely responsible for the dynamics in debt maturity. Beyond that, our results show that there's a natural inertia in short debt maturity firms who show extreme reliance on short-term financing. This finding is in conformity with the strand of research such as Brunnermeier and Oehmke (2013) demonstrating "inefficiently short-term equilibrium financing". The empirical evidence of Custodio et al. (2013) presents that the excessive reliance on short-term debt is more serious for small firms. Our separate analyses for micro, small and big firms (unreported for brevity) however show that this is true for all scales of firms, with big firms more prominent, small firms the next and micro firms the last.

5. Conclusion

This paper re-examines the debt maturity determinants issue by exploiting the motivations behind debt maturity dynamics and traces the implications of managerial targeting incentives through to debt maturity. Our main findings are three-fold. First, we find important features of convergence and persistence for debt maturity evolution in event time. Particularly, we show that the convergence is driven by a transitory component that is probably associated with firms' incentives to approach the debt maturity target. Second, our regression results demonstrate that the targeting incentive explains a large amount of cross-sectional variation in debt maturity changes and the effect persists through time. Third, targeting pattern coexists with mechanical mean reversion. Removing the effect of debt maturity targeting, we find that long debt maturity users switch to employ more short-term debts while short debt maturity users continue to employ more short-term debts.

This research complements the work of Ozkan (2000), Antoniou et al. (2006), Cai et al. (2008) and Terra (2011) by exploiting the implications of debt maturity target through examining debt maturity evolution and explicitly studying the significance of debt maturity targeting relative to the conventional determinants. Further, our evidence corroborates Leary and Roberts (2014) in the relevance of the peer firms' financing policies and He and Xiong (2012b), Brunnermeier and Oehmke (2013) in the inefficiently short-term equilibrium financing.

The current study could also shed some light on future studies concerning different moments of debt refinancing. One interesting direction is to examine whether managerial incentive to time the market plays a role in debt maturity decisions of firms and how this force interacts with the targeting incentive. We leave the question open for future research.

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Table I

Variable Definitions

Variables	Abbreviation	Measurement
Size	SIZE	Relative Size = The percentage of NYSE firms that have the same or smaller market capitalization.
Asset Maturity	AMAT	Weighted Average Maturity of Assets = (Current Assets ÷ Total Book Assets) × (Current Assets ÷ Cost of Goods Sold) + (Net Property Plant & Equipment ÷ Total Book Assets)×(Net Property Plant & Equipment ÷ Depreciation & Amortization).
Leverage	LEV	Book Leverage = The ratio of a firm's total debt outstanding to the book value of total assets.
Market-to-Book	MTB	Market-to-Book Ratio = (Book Value of Total Assets – Book Value of Common Equity + Market Value of Common Equity) ÷ Book Value of Total Assets.
R&D	R&D	R&D Ratio = The ratio of a firm's R&D expenses to the book value of total assets.
R&D Dummy	R&D Dummy	R&D Dummy is defined as a dummy variable which takes a value of one if a firm report positive R&D expense and zero otherwise.
Industry	INDUSTRY	A set of industry dummies according to 48 Fama-French industry classification.
Public Credit Access	ACCESS	Public credit access is defined as a dummy variable which takes a value of one if Standard and Poor's Domestic Long-Term Issuer Rating is available and zero otherwise.
Cumulative Stock Return	RETURN	Cumulative stock return is the cumulative log return on the stock over the previous years.
Stock Return Volatility	VOLAT	Stock return volatility is the monthly stock return standard deviation over the previous year(s).
Target Debt Maturity	$DMAT^{T}$	Target debt maturity is the weighted average debt maturity of other firms in the same industry, with each firm weighted by its total liabilities. Industry is defined based on Fama French 48 industry classification.
Debt Maturity Target Deviation	DMATD	Debt maturity target deviation is the difference between the observed and the target debt maturity.
Short Debt Maturity Dummy	SHORT	Short debt maturity is a dummy variable which takes a value of one if debt maturity of a firm is present at the 10^{th} debt maturity percentile, and zero otherwise.
Long Debt Maturity Dummy	LONG	Long debt maturity is a dummy variable which takes a value of one if debt maturity of a firm is present at the 90^{th} debt maturity percentile, and zero otherwise.
Negative Debt Maturity Target Deviation	NEG	Negative debt maturity target deviation is a dummy variable which takes a value of one if debt maturity target deviation of a firm is negative, and zero otherwise.

Table II

Descriptive Statistics

This table documents mean, median and standard deviation (SD) for variables in differences (first, third and fifth respectively), accumulations and prior levels. The weighted average debt maturity structure is calculated according to Equation (1). All the other variables are defined in Table I. SIZE, AMAT, LEV, MTB, and R&D are winsorized at the 1st and 99th percentiles. Analysis is performed based on the 1-year, 3-year and 5-year timelines. Debt maturity target deviation is measured as of 1 year, 3 years and 5 years prior to the observation year t. The sample consists of 5828 U.S. listed & based non-financial non-utility firms in the CRSP/Compustat Merged database over the period 1986-2011.

	Differences								
	First Differences			**Third Differences**			**Fifth Differences**		
Variables	mean	median	SD	mean	median	SD	mean	median	SD
DMAT	-0.03	0.00	1.83	-0.06	0.00	2.58	-0.10	0.00	2.87
SIZE	0.10	-0.05	7.74	0.24	-0.10	12.20	0.71	-0.09	14.75
AMAT	-0.09	-0.06	3.48	-0.21	-0.13	4.37	-0.30	-0.19	4.68
LEV	0.00	0.00	0.27	0.01	0.00	0.33	0.01	0.00	0.36
MTB	-0.05	-0.01	1.48	-0.12	-0.03	1.85	-0.18	-0.04	1.94
R&D	0.00	0.00	0.06	0.00	0.00	0.08	0.00	0.00	0.08
ACCESS	0.01	0.00	0.14	0.02	0.00	0.24	0.03	0.00	0.29
$DMAT^{T}$	0.03	-0.00	0.73	0.07	0.06	1.01	0.09	0.05	1.13
	Accumulations								
	Over the Last Year			Over the Last Three Years			Over the Last Five Years		
Variables	mean	median	SD	mean	median	SD	mean	median	SD
RETURN	0.18	0.04	0.93	0.49	0.10	1.97	0.84	0.17	3.20
VOLAT	0.15	0.13	0.11	0.16	0.14	0.10	0.16	0.14	0.09
	Prior Levels								
	One Year Ago			Three Year Ago			Five Year Ago		
Variables	mean	median	SD	mean	median	SD	mean	median	SD
DMATD	-1.01	-1.67	3.04	-0.89	-1.47	3.03	-0.78	-1.27	3.01

Table III

The Distribution of Survivor Firms throughout Debt Maturity Portfolios in Event Time

This table exhibits the distribution of survivor firms in percentage throughout debt maturity portfolios in event time for initially short, medium, long and very long debt maturity portfolios. Debt maturity is calculated according to Equation (1). We focus on a group of firms who have complete debt maturity information for the entire 20-year event time period. The portfolios are constructed based on firms' weighted average debt maturity. Event time 0 denotes the portfolio formation year and event time s denotes the s^{th} year subsequent to the portfolio formation year. The curves represent the percentage of firms that remain in a specific debt maturity portfolio. Below is the portfolio formation procedure. Each year, we sort firms by debt maturity levels and split them into four equal groups. Then for each portfolio that is constructed in a given year, we calculate the percentage of firms who are present in a specific portfolio for the subsequent 20 years. The portfolio composition remains strictly unchanged. For each year from 1974 to 1991, we repeat the above sorting and averaging procedure, which generates 18 sets of event-time percentages for each portfolio. We next calculate the mean of the event-time percentages across event time. The sample consists of 1083 U.S. listed & based non-financial non-utility firms in the CRSP/Compustat Merged database.

		Event Time																			
Innitially	Subsequently	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Short	Short	79,85	72,76	68,22	64,03	61,39	59,14	58,30	56,90	55,52	54,86	53,65	52,57	50,79	50,58	50,27	49,46	50,55	49,24	48,75	48,72
Short	Medium	13,03	14,65	16,72	18,56	19,28	20,06	19,76	20,48	21,33	22,40	23,38	24,30	24,61	24,58	25,57	26,36	25,59	26,81	26,07	25,00
Short	Long	4,27	7,06	8,02	9,03	10,09	10,71	11,12	11,15	12,00	12,07	12,57	12,26	14,31	14,21	12,88	12,76	11,89	11,67	11,99	12,73
Short	Very Long	3,41	6,39	7,91	8,37	9,15	9,86	11,40	11,51	11,38	10,73	10,71	10,13	10,83	11,11	10,75	11,09	12,69	12,37	12,84	12,94
Medium	Short	16,62	20,92	22,37	22,86	22,56	22,32	22,46	22,01	22,47	21,30	22,76	22,56	24,20	22,91	23,65	23,73	23,32	24,16	24,30	23,64
Medium	Medium	57,11	44,86	38,89	36,87	35,49	34,25	32,01	32,63	32,20	32,30	30,69	30,54	28,74	29,39	30,21	29,80	30,57	30,31	29,84	30,27
Medium	Long	17,71	22,50	24,73	24,95	25,79	25,01	27,01	25,55	26,13	25,45	24,83	24,42	24,77	25,66	24,85	25,25	25,10	24,32	24,98	25,80
Medium	Very Long	8,56	11,72	14,01	15,32	16,15	18,41	18,51	19,82	19,20	20,96	21,73	22,48	22,28	22,04	21,29	21,22	21,01	21,20	20,89	20,30
Long	Short	3,07	4,63	7,47	8,58	10,51	12,47	12,29	12,32	12,96	13,55	13,43	13,63	14,04	14,40	14,12	14,19	13,98	14,61	15,23	16,51
Long	Medium	25,03	30,27	30,60	28,55	28,51	26,95	28,97	27,92	26,13	26,14	25,55	25,05	25,76	24,97	22,96	24,13	24,52	25,03	24,92	25,40
Long	Long	55,07	43,87	37,81	36,92	33,82	34,68	31,95	31,97	32,32	31,54	32,66	31,99	30,49	29,93	32,81	31,65	32,35	31,77	32,24	31,58
Long	Very Long	17,86	21,76	25,39	26,05	27,76	25,97	27,41	27,13	28,67	28,42	28,71	28,93	30,28	30,61	30,08	29,93	29,42	28,63	27,59	27,52
Very Long	Short	2,10	2,67	3,88	5,86	6,07	6,71	7,08	8,73	8,63	10,16	10,28	11,53	11,81	11,72	11,45	12,42	11,62	11,73	11,36	11,14
Very Long	Medium	5,18	10,35	14,23	16,32	16,79	18,66	19,24	19,18	20,27	19,67	20,73	19,77	21,14	21,30	21,41	19,45	19,51	17,74	19,49	19,35
Very Long	Long	23,37	26,88	29,94	29,41	30,78	29,91	30,52	31,88	29,78	31,35	30,34	31,67	30,94	30,58	29,91	30,64	31,04	32,75	31,29	30,35
Very Long	Very Long	70,43	60,83	53,22	50,11	46,53	45,39	42,85	41,24	40,94	39,76	38,96	37,57	36,81	36,54	37,07	37,31	37,38	37,56	38,07	38,41

Table IV

Debt Maturity Changes Categorized by Debt Maturity Target Deviation

This table displays the mean and median (reported in (parentheses)) value of previous debt maturity target deviation and debt maturity changes for quartiles constructed based on previous debt maturity target deviation. Number of observations is in [brackets]. To test if changes in debt maturity are different from zero at conventional significance levels, we conduct student's t-test for the mean changes and Wilcoxon signed-rank test for the median changes. ***, ** and * show that changes in debt maturity is significantly different from zero at 1%, 5% and 10% level respectively. The weighted average debt maturity structure is calculated according to Equation (1). Analysis is performed based on the 1-year, 3-year and 5-year timelines. Debt maturity target deviation is measured as of 1 year, 3 years and 5 years prior to the observation year t. The sample consists of 5828 U.S. listed & based non-financial non-utility firms in the CRSP/Compustat Merged database over the period 1986-2011.

Target Deviation Quartile	Previous Debt Maturity Target			Debt Maturity Changes		
	1-Year	3-Year	5-Year	1-Year	3-Year	5-Year
	-4.43	-4.36	-4.28	0.47***	0.88***	1.13***
Lowest Quartile	(-4.26)	(-4.19)	(-4.12)	(0.00)***	(0.00)***	(0.00)***
	[17047]	[14348]	[11715]	[16217]	[13295]	[10684]
	-2.62	-2.54	-2.46	0.33***	0.65***	0.79***
Quartile 2	(-2.66)	(-2.58)	(-2.50)	(0.00)	(0.00)***	(0.00)***
	[17048]	[14349]	[11715]	[16275]	[13288]	[10651]
	-0.28	-0.17	-0.04	-0.04***	-0.06***	-0.12***
Quartile 3	(-0.31)	(-0.20)	(-0.07)	(-0.32)***	(-0.32)***	(-0.34)***
	[17048]	[14349]	[11715]	[16479]	[13517]	[10862]
	3.29	3.36	3.42	-0.86***	-1.71***	-2.11***
Highest Quartile	(3.02)	(3.08)	(3.15)	(-0.37)***	(-1.26)***	(-1.76)***
	[17047]	[14348]	[11715]	[16433]	[13426]	[10808]

Table V

Pearson Correlations

This table reports Pearson correlation coefficients between debt maturity changes and changes in conventional debt maturity determinants, changes in peer firms' debt maturity, and previous deviation from peer firms' debt maturity. ***, ** and * show that two variables are significantly correlated at 1%, 5% and 10% levels respectively. The weighted average debt maturity structure is calculated according to Equation (1). All the other variables are defined in Table I. SIZE, AMAT, LEV, MTB, and R&D are winsorized at the 1st and 99th percentiles. Analysis is performed based on the 1-year, 3-year and 5-year timelines. Debt maturity target deviation is measured as of 1 year, 3 years and 5 years prior to the observation year t. The sample consists of 5828 U.S. listed & based non-financial non-utility firms in the CRSP/Compustat Merged database over the period 1986-2011.

	$\Delta DMAT_{t,t-s}$		
Variables	s=1	s=3	s=5
$\Delta SIZE_{t,t-s}$	0.03^{***}	0.04^{***}	0.05^{***}
$\Delta AMAT_{t,t-s}$	0.03^{***}	0.04^{***}	0.04^{***}
$\Delta LEV_{t,t-s}$	0.08^{***}	0.12^{***}	0.15^{***}
$\Delta MTB_{t,t-s}$	-0.03^{***}	-0.04^{***}	-0.05^{***}
$\Delta R\&D_{t,t-s}$	-0.01^{***}	-0.02^{***}	-0.02^{***}
$\Delta ACCESS_{t,t-s}$	0.09^{***}	0.17^{***}	0.19^{***}
$RETURN_{t,t-s}$	0.02^{***}	0.04^{***}	0.02^{***}
$VOLAT_{t,t-s}$	-0.01^{***}	-0.01^{*}	0.00

Table VI

The Driving forces of Debt Maturity Dynamics:

Conventional Debt Maturity Determinants

This table presents the regression results for the following empirical model:

Model (3): $DMAT_{i,t} - DMAT_{i,t-s} = \alpha + \beta_1 \Delta SIZE_{i,t,t-s} + \beta_2 \Delta AMAT_{i,t,t-s} + \beta_3 \Delta LEV_{i,t,t-s} + \beta_4 \Delta MTB_{i,t,t-s} + \beta_5 \Delta R\&D_{i,t,t-s} + \beta_6 \Delta ACCESS_{i,t,t-s} + \beta_7 RETURN_{i,t,t-s} + \beta_8 VOLAT_{i,t,t-s} + \varepsilon_{i,t} \quad i = 1, \ldots, n \;\; t = 1, \ldots, T$

The coefficients are estimated by running Fama-Macbeth regressions. Newey-West adjusted standard errors are reported in (parentheses). ***, ** and * show that the coefficient is significant at 1%, 5% and 10% level respectively. The weighted average debt maturity structure is calculated according to Equation (1). All the other variables are defined in Table I. SIZE, AMAT, LEV, MTB, and R&D are winsorized at the 1st and 99th percentiles. The sample consists of 5828 U.S. listed & based non-financial non-utility firms in the CRSP/Compustat Merged database over the period 1986-2011.

	$\Delta DMAT_{t,t-s}$		
Variable	s=1	s=3	s=5
Intercept	-0.02	-0.17*	-0.22*
	(0.03)	(0.09)	(0.13)
$\Delta SIZE_{t,t-s}$	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)
$\Delta AMAT_{t,t-s}$	0.01***	0.02***	0.02***
	(0.00)	(0.01)	(0.00)
$\Delta LEV_{t,t-s}$	2.41***	2.88***	3.08***
	(0.21)	(0.24)	(0.25)
$\Delta MTB_{t,t-s}$	-0.09***	-0.12***	-0.10***
	(0.01)	(0.02)	(0.01)
$\Delta R\&D_{t,t-s}$	-0.11	-0.31**	-0.45**
	(0.12)	(0.11)	(0.18)
$\Delta ACCESS_{t,t-s}$	1.03***	1.53***	1.54***
	(0.09)	(0.07)	(0.07)
$RETURN_{t,t-s}$	0.14***	0.08***	0.03**
	(0.02)	(0.02)	(0.01)
$VOLAT_{t,t-s}$	-0.32**	0.00	0.20
	(0.15)	(0.35)	(0.51)
Adj. R^2	0.036	0.072	0.087
Obs.	61902	50462	40486

Table VII

The Driving forces of Debt Maturity Dynamics:

Conventional Determinants or Firm's Incentive to Approach Target Debt Maturity

This table presents the regression results (in Panel A) and the sensitivity analysis (in Panel B) on the extent to which conventional debt maturity determinants and firm's incentive to approach peer firms' debt maturity affect debt maturity adjustment of firms. The models to estimate are specified as follows.

Model (4): $DMAT_{i,t} - DMAT_{i,t-s} = \alpha + \lambda_1 DMATD_{i,t-s} + \varepsilon_{i,t} \quad i = 1, \dots, n \;\; t = 1, \dots, T$

Model (5): $DMAT_{i,t} - DMAT_{i,t-s} = \alpha + \lambda_1 DMATD_{i,t-s} + \lambda_2 \Delta DMAT^{T}_{i,t,t-s} + \varepsilon_{i,t} \quad i = 1, \dots, n \;\; t = 1, \dots, T$

Model (6): $DMAT_{i,t} - DMAT_{i,t-s} = \alpha + \beta_1 \Delta SIZE_{i,t,t-s} + \beta_2 \Delta AMAT_{i,t,t-s} + \beta_3 \Delta LEV_{i,t,t-s} + \beta_4 \Delta MTB_{i,t,t-s} + \beta_5 \Delta R\&D_{i,t,t-s} + \beta_6 \Delta ACCESS_{i,t,t-s} + \beta_7 RETURN_{i,t,t-s} + \beta_8 VOLAT_{i,t,t-s} + \lambda_1 DMATD_{i,t-s} + \lambda_2 \Delta DMAT^{T}_{i,t,t-s} + \varepsilon_{i,t} \quad i = 1, \dots, n \;\; t = 1, \dots, T$

The coefficients are estimated by running Fama-Macbeth regressions. Newey-West adjusted standard errors are reported in (parentheses). ***, ** and * show that the coefficient is significant at 1%, 5% and 10% level respectively. The weighted average debt maturity structure is calculated according to Equation (1). All the other variables are defined in Table I. SIZE, AMAT, LEV, MTB, and R&D are winsorized at the 1st and 99th percentiles. Debt maturity target deviation is measured as of 1 year, 3 years and 5 years prior to the observation year t. The sample consists of 5828 U.S. listed & based non-financial non-utility firms in the CRSP/Compustat Merged database over the period 1986-2011.

	Panel A: Regression results								
	$\Delta DMAT_{t,t\text{-}s}$								
	s=1			s=3			s=5		
Variable	Model (4)	Model (5)	Model (6)	Model (4)	Model (5)	Model (6)	Model (4)	Model (5)	Model (6)
Intercept	-0.22***	-0.22***	-0.06**	-0.39***	-0.42***	-0.10	-0.47***	-0.52***	-0.01
	(0.04)	(0.04)	(0.03)	(0.08)	(0.08)	(0.07)	(0.09)	(0.09)	(0.08)
$DMATD_{t\text{-}s}$	-0.18***	-0.18***	-0.19***	-0.35***	-0.36***	-0.37***	-0.44***	-0.46***	-0.47***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\Delta DMAT^{T}_{t,t\text{-}s}$		0.09***	0.10***		0.20***	0.23***		0.24***	0.26***
		(0.01)	(0.01)		(0.03)	(0.02)		(0.03)	(0.02)
$\Delta SIZE_{t.t\text{-}s}$			0.01***			0.01***			0.01***
			(0.00)			(0.00)			(0.00)
$\Delta AMAT_{t.t\text{-}s}$			0.01***			0.01***			0.01***
			(0.00)			(0.00)			(0.00)
$\Delta LEV_{t.t\text{-}s}$			2.27***			2.48***			2.47***
			(0.20)			(0.20)			(0.19)
$\Delta MTB_{t.t\text{-}s}$			-0.08***			-0.07***			-0.03**
			(0.01)			(0.01)			(0.01)
$\Delta R\&D_{t.t\text{-}s}$			-0.29**			-0.53***			-0.75***
			(0.12)			(0.13)			(0.20)
$\Delta ACCESS_{t.t\text{-}s}$			1.02***			1.41***			1.37***
			(0.10)			(0.11)			(0.13)
$RETURN_{t.t\text{-}s}$			0.14***			0.07***			0.02*
			(0.02)			(0.02)			(0.01)
$VOLAT_{t.t\text{-}s}$			-1.38***			-2.72***			-3.69***
			(0.18)			(0.38)			(0.43)
Adj. R^2	0.090	0.092	0.128	0.171	0.177	0.246	0.212	0.219	0.297
Obs.	65524	65518	61861	57420	57410	50416	48938	48928	40435

Table VII *(continued)*

One standard deviation change in	*Panel B: Magnitude effect*								
	$\Delta DMAT_{t,t-s}$								
	s=1			s=3			s=5		
	Model (4)	Model (5)	Model (6)	Model (4)	Model (5)	Model (6)	Model (4)	Model (5)	Model (6)
$DMATD_{t-s}$	-0.55	-0.55	-0.58	-1.06	-1.09	-1.12	-1.32	-1.38	-1.41
$\Delta DMAT^{T}_{t,t-s}$		0.07	0.07		0.20	0.23		0.27	0.29
$\Delta SIZE_{t,t-s}$			0.08			0.12			0.15
$\Delta AMAT_{t,t-s}$			0.03			0.04			0.05
$\Delta LEV_{t,t-s}$			0.61			0.82			0.89
$\Delta MTB_{t,t-s}$			-0.12			-0.13			-0.06
$\Delta R\&D_{t,t-s}$			-0.02			-0.04			-0.06
$\Delta ACCESS_{t,t-s}$			0.14			0.34			0.40
$RETURN_{t.t-s}$			0.13			0.14			0.06
$VOLAT_{t.t-s}$			-0.15			-0.27			-0.33

Table VIII

Firm's Incentive to Approach Target Debt Maturity and the Role of Extreme Cases

This table examines the role of extreme cases in debt maturity adjustment decisions of firms. Extreme cases are defined as firms who are present at the 10th and 90th percentile in the annual debt maturity distribution. The models to estimate are specified as follows.

Model (6): $DMAT_{i,t} - DMAT_{i,t-s} = \alpha + \beta_1 \Delta SIZE_{i,t,t-s} + \beta_2 \Delta AMAT_{i,t,t-s} + \beta_3 \Delta LEV_{i,t,t-s} + \beta_4 \Delta MTB_{i,t,t-s} + \beta_5 \Delta R\&D_{i,t,t-s} + \beta_6 \Delta ACCESS_{i,t,t-s} + \beta_7 RETURN_{i,t,t-s} + \beta_8 VOLAT_{i,t,t-s} + \lambda_1 DMATD_{i,t-s} + \lambda_2 \Delta DMAT^{T}_{i,t,t-s} + \varepsilon_{i,t} \quad i = 1, \ldots, n \ \ t = 1, \ldots, T$

Model (7): $DMAT_{i,t} - DMAT_{i,t-s} = \alpha + \beta_1 \Delta SIZE_{i,t,t-s} + \beta_2 \Delta AMAT_{i,t,t-s} + \beta_3 \Delta LEV_{i,t,t-s} + \beta_4 \Delta MTB_{i,t,t-s} + \beta_5 \Delta R\&D_{i,t,t-s} + \beta_6 \Delta ACCESS_{i,t,t-s} + \beta_7 RETURN_{i,t,t-s} + \beta_8 VOLAT_{i,t,t-s} + \gamma_1 SHORT_{i,t-s} + \gamma_2 LONG_{i,t-s} + \varepsilon_{i,t} \quad i = 1, \ldots, n \ \ t = 1, \ldots, T$

Model (8): $DMAT_{i,t} - DMAT_{i,t-s} = \alpha + \beta_1 \Delta SIZE_{i,t,t-s} + \beta_2 \Delta AMAT_{i,t,t-s} + \beta_3 \Delta LEV_{i,t,t-s} + \beta_4 \Delta MTB_{i,t,t-s} + \beta_5 \Delta R\&D_{i,t,t-s} + \beta_6 \Delta ACCESS_{i,t,t-s} + \beta_7 RETURN_{i,t,t-s} + \beta_8 VOLAT_{i,t,t-s} + \lambda_1 DMATD_{i,t-s} + \lambda_2 \Delta DMAT^{T}_{i,t,t-s} + \gamma_1 SHORT_{i,t-s} + \gamma_2 LONG_{i,t-s} + \varepsilon_{i,t} \quad i = 1, \ldots, n \ \ t = 1, \ldots, T$

Model (6) documents the results by excluding extreme cases. Model (7) and Model (8) document the results for all our sample firms. The coefficients are estimated by running Fama-Macbeth regressions. Newey-West adjusted standard errors are reported in (parentheses). ***, ** and * show that the coefficient is significant at 1%, 5% and 10% level respectively. The weighted average debt maturity structure is calculated according to Equation (1). SHORT is a dummy variable which takes a value of 1 if debt maturity of a firm is at the 10th debt maturity percentile. LONG is a dummy variable which takes a value of 1 if debt maturity of a firm is at the 90th debt maturity percentile. All the other variables are defined in Table I. SIZE, AMAT, LEV, MTB, and R&D are winsorized at the 1st and 99th percentiles. Debt maturity target deviation is measured as of 1 year, 3 years and 5 years prior to the observation year t. The sample consists of 5828 U.S. listed & based non-financial non-utility firms in the CRSP/Compustat Merged database over the period 1986-2011.

	$\Delta DMAT_{t,t-s}$								
	s=1			s=3			s=5		
Variable	Model (6)	Model (7)	Model (8)	Model (6)	Model (7)	Model (8)	Model (6)	Model (7)	Model (8)
Intercept	0,04	0,14***	0,04	0,08	0,19	0,08	0,22**	0,23	0,18*
	(0,03)	(0,05)	(0,03	(0,08)	(0,12)	(0,07)	(0,09)	(0,16)	(0,09)
$DMATD_{t-s}$	-0,16***		-0,16***	-0,32***		-0,32***	-0,41***		-0,40***
	(0,01)		(0,00)	(0,01)		(0,01)	(0,01)		(0,00)
$\Delta DMAT^{T}_{t,t-s}$	0,08***		0,08***	0,20***		0,20***	0,25***		0,23***
	(0,02)		(0,01)	(0,01)		(0,02)	(0,01)		(0,02)
$\Delta SIZE_{t.t-s}$	0,01***	0,01***	0,01***	0,01***	0,01***	0,01***	0,01***	0,01***	0,01***
	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)
$\Delta AMAT_{t.t-s}$	0,02***	0,01***	0,01***	0,02***	0,01***	0,01***	0,02***	0,01***	0,01***
	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)	(0,00)
$\Delta LEV_{t.t-s}$	2,15***	2,38***	2,32***	2,28***	2,71***	2,57***	2,24***	2,82***	2,59***
	(0,28)	(0,23)	(0,21)	(0,22)	(0,25)	(0,21)	(0,19)	(0,25)	(0,21)
$\Delta MTB_{t.t-s}$	-0,09***	-0,09***	-0,08***	-0,08***	-0,10***	-0,08***	-0,04**	-0,08***	-0,04***
	(0,01)	(0,01)	(0,01)	(0,01)	(0,02)	(0,01)	(0,02)	(0,01)	(0,01)
$\Delta R\&D_{t.t-s}$	-0,35**	-0,17	-0,26**	-0,52**	-0,42***	-0,50***	-0,64***	-0,59***	-0,67***
	(0,13)	(0,13)	(0,11)	(0,22)	(0,12)	(0,13)	(0,20)	(0,20)	(0,19)
$\Delta ACCESS_{t.t-s}$	1,02***	1,03***	1,02***	1,47***	1,44***	1,37***	1,42***	1,41***	1,32***
	(0,11)	(0,09)	(0,10)	(0,11)	(0,07)	(0,10)	(0,14)	(0,09)	(0,12)
$RETURN_{t.t-s}$	0,15***	0,14***	0,14***	0,08***	0,08***	0,08***	0,01	0,02**	0,02*
	(0,02)	(0,02)	(0,02)	(0,02)	(0,02)	(0,02)	(0,01)	(0,01)	(0,01)
$VOLAT_{t.t-s}$	-1,33***	-0,67***	-1,33***	-2,53***	-0,91**	-2,60***	-3,76***	-1,07**	-3,50***
	(0,12)	(0,14)	(0,16)	(0,31)	(0,35)	(0,35)	(0,33)	(0,44)	(0,39)
$SHORT_{t-s}$		0,24***	-0,10***		0,62***	-0,15		0,81***	-0,32***
		(0.07)	(0,03)		(0,10)	(0,12)		(0,12)	(0,09)
$LONG_{t-s}$		-1,41***	-0,52***		-2,76***	-1,05***		-3,32***	-1,19***
		(0,12)	(0,10)		(0,24)	(0.19)		(0,22)	(0,16)
Adj. R^2	0.090	0.096	0.134	0.169	0.189	0.258	0.205	0.223	0.310
Obs.	49784	61902	61861	40223	50455	50416	31905	40472	40435

Table IX

Firm's Incentive to Approach Target Debt Maturity:

Positive Deviation versus Negative Deviation

This table tests whether the negative deviation from peer firms' debt maturity affects debt maturity adjustment decisions of firms the same way as the positive deviation. The model to estimate is specified as follows.

Model (9): $DMAT_{i,t} - DMAT_{i,t-s} = \alpha + \beta_1 \Delta SIZE_{i,t,t-s} + \beta_2 \Delta AMAT_{i,t,t-s} + \beta_3 \Delta LEV_{i,t,t-s} + \beta_4 \Delta MTB_{i,t,t-s} + \beta_5 \Delta R\&D_{i,t,t-s} + \beta_6 \Delta ACCESS_{i,t,t-s} + \beta_7 RETURN_{i,t,t-s} + \beta_8 VOLAT_{i,t,t-s} + \lambda_1 DMATD_{i,t-s} + \lambda_2 \Delta DMAT^T_{i,t,t-s} + \gamma_1 SHORT_{i,t-s} + \gamma_2 LONG_{i,t-s} + \lambda_3 NEG_{i,t-s} + \lambda_4 NEG_{i,t-s} \times DMATD_{i,t-s} + \varepsilon_{i,t} \quad i = 1, \dots, n \;\; t = 1, \dots, T$

The parameter of interest isλ_4. For brevity, estimates are only reported forλ_1, λ_3 andλ_4. The coefficients are estimated by running Fama-Macbeth regressions. Newey-West adjusted standard errors are reported in (parentheses). ***, ** and * show that the coefficient is significant at 1%, 5% and 10% level respectively. The weighted average debt maturity structure is calculated according to Equation (1). SHORT is a dummy variable which takes a value of 1 if debt maturity of a firm is at the 10th debt maturity percentile. LONG is a dummy variable which takes a value of 1 if debt maturity of a firm is at the 90th debt maturity percentile. NEG is a dummy variable which takes a value of one if debt maturity target deviation of a firm is negative. $NEG \times DMATD$ is the interaction item between the negative debt maturity target deviation dummy and debt maturity target deviation All the other variables are defined in Table I. SIZE, AMAT, LEV, MTB, and R&D are winsorized at the 1st and 99th percentiles. Debt maturity target deviation is measured as of 1 year, 3 years and 5 years prior to the observation year t. The sample consists of 5828 U.S. listed & based non-financial non-utility firms in the CRSP/Compustat Merged database over the period 1986-2011.

	$\Delta DMAT_{t,t-s}$		
	s=1	s=3	s=5
λ_1	-0.18***	-0.37***	-0.50***
	(0.02)	(0.03)	(0.04)
λ_3	0.12**	0.26***	0.19**
	(0.05)	(0.06)	(0.07)
λ_4	0.06**	0.14***	0.20***
	(0.03)	(0.05)	(0.05)

Table X

Firm's Incentive to Approach Target Debt Maturity:

Alternative Debt Maturity Target Proxies

This table examines firm's incentive to approach target debt maturity with alternative target proxies. The models to estimate are specified as follows.

Model (12): $DMAT_{i,t} - DMAT_{i,t-s} = \alpha + \lambda_1 DMATD_{i,t-s} + \lambda_2 \Delta DMAT^T_{i,t,t-s} + \gamma_1 SHORT_{i,t-s} + \gamma_2 LONG_{i,t-s} + \varepsilon_{i,t} \quad i = 1, \dots, n \;\; t = 1, \dots, T$

Model (13): $DMAT_{i,t} - DMAT_{i,t-s} = \alpha + \lambda_1 DMATD_{i,t-s} + \lambda_2 \Delta DMAT^T_{i,t,t-s} + \gamma_1 SHORT_{i,t-s} + \gamma_2 LONG_{i,t-s} + \lambda_3 NEG_{i,t-s} + \lambda_4 NEG_{i,t-s} \times DMATD_{i,t-s} + \varepsilon_{i,t} \quad i = 1, \dots, n \;\; t = 1, \dots, T$

In the column "OLS", debt maturity target is estimated as the fitted value from the OLS regression based on firm's historical panel information, specified as follows, $DMAT_{i,t} = \alpha_\theta + \beta_{1\theta} Size_{i,t-1} + \beta_{2\theta} Leverage_{i,t-1} + \beta_{3\theta} Asset\ Maturity_{i,t-1} + \beta_{4\theta}\ Market - to - Book_{i,t-1} + \beta_{5\theta} R\&D_{i,t-1} + \gamma_\theta Industry_i + \varepsilon_{i,t} \quad i = 1, \dots, n \;\; t = 1, \dots, T$. The target debt maturity for the firm i in year t is computed by applying the coefficient estimates to firm i's characteristics measured as of year t-1. In the column "QR", debt maturity target is estimated as the fitted value from the 25th, 50th and 75th quantile regressions based on firm's historical panel information, specified as follows, $(DMAT_{i,t} | X_{i,t-1}) = \alpha_\theta + \beta_{1\theta} Size_{i,t-1} + \beta_{2\theta} Leverage_{i,t-1} + \beta_{3\theta} Asset\ Maturity_{i,t-1} + \beta_{4\theta} Market - to - Book_{i,t-1} + \beta_{5\theta} R\&D_{i,t-1} + \gamma_{i\theta} Industry_i + \varepsilon_{i,t} \quad i = 1, \dots, n \;\; t = 1, \dots, T$. The target debt maturity for the firm i in year t is computed by applying the coefficient estimates of the corresponding debt maturity quantile to firm i's characteristics measured as of year t-1. That is, the 25th quantile regression results apply to $DMAT_{t-1}$ inferior to the 0.25 percentile, the 50th quantile regression results apply to $DMAT_{t-1}$ superior to the 0.25 percentile and inferior to the 0.75 percentile, and the 75th quantile regression results apply to $DMAT_{t-1}$ superior to the 0.75 percentile. In the column "Past Mean", debt maturity target is estimated as the time-series average of a firm's historical debt maturities. The coefficients are estimated by running Fama-Macbeth regressions. Newey-West adjusted standard errors are reported in (parentheses). ***, ** and * show that the coefficient is significant at 1%, 5% and 10% level respectively. The weighted average debt maturity structure is calculated according to Equation (1). SHORT is a dummy variable which takes a value of 1 if debt maturity of a firm is at the 10th debt maturity percentile. LONG is a dummy variable which takes a value of 1 if debt maturity of a firm is at the 90th debt maturity percentile. All the other variables are defined in Table I. SIZE, AMAT, LEV, MTB, and R&D are winsorized at the 1st and 99th percentiles. Debt maturity target deviation is measured as of 1 year, 3 years and 5 years prior to the observation year t. The sample consists of 5828 U.S. listed & based non-financial non-utility firms in the CRSP/Compustat Merged database over the period 1986-2011.

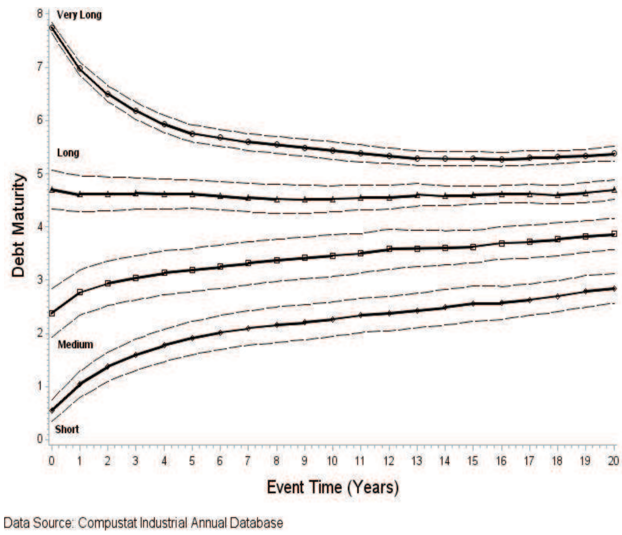
	$\Delta DMAT_{t,t-s}$								
	Panel A : Model 1								
	s=1			s=3			s=5		
Variable	OLS	QR	Past Mean	OLS	QR	Past Mean	OLS	QR	Past Mean
Intercept	-0.10***	-0.08*	-0.01	-0.18**	-0.13	-0.09	-0.19**	-0.16	-0.11*
	(0.03)	(0.04)	(0.03)	(0.06)	(0.08)	(0.05)	(0.07)	0.10	(0.06)
$DMATD_{t-s}$	-0.26***	-0.30***	-0.21***	-0.53***	-0.52***	-0.89***	-0.66***	-0.61***	-1.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
$\Delta DMAT^T_{t,t-s}$	0.19***	0.98***	-0.01	0.61***	1.03***	1.92***	0.73***	1.03***	1.82***
	(0.01)	(0.03)	(0.06)	(0.03)	(0.02)	(0.05)	(0.03)	(0.02)	(0.05)
$SHORT_{t-s}$	-0.00	0.21***	0.20***	-0.07	0.08	0.48***	-0.21	0.17*	0.53***
	(0.01)	(0.06)	(0.06)	(0.09)	(0.10)	(0.05)	(0.14)	(0.09)	(0.12)
$LONG_{t-s}$	-0.15***	-0.27***	-0.65***	-0.29**	-0.59***	-0.90***	-0.32***	-0.70***	-0.90***
	(0.05)	(0.05)	(0.06)	(0.11)	(0.13)	(0.11)	(0.09)	(0.14)	(0.08)
Adj. R^2	0.127	0.416	0.106	0.275	0.557	0.358	0.341	0.605	0.444
Obs.	59535	59517	61525	51216	51201	52941	42481	42466	43830
	Panel B : Model 2, Positive Deviation versus Negative Deviation								
λ_4	0.08***	0.08***	0.06***	0.16***	0.14***	0.24***	0.21***	0.13***	0.25***
	(0.01)	(0.03)	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)

Figure I

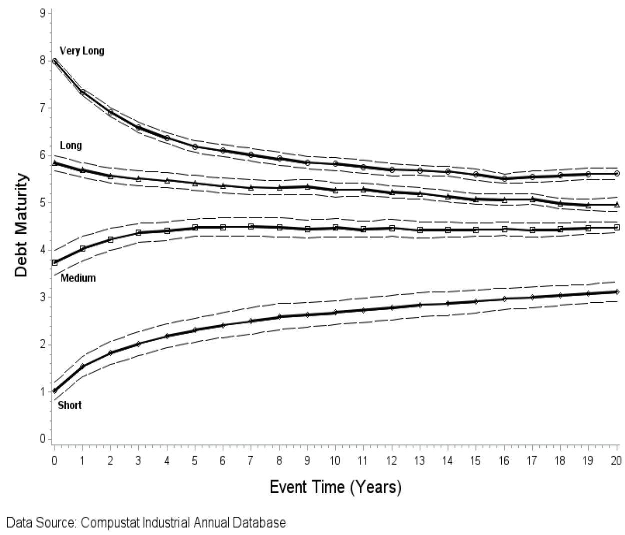
Average Debt Maturity of Actual Debt Maturity Portfolios in Event Time

This figure exhibits average debt maturity in event time for four portfolios constructed based on firms' weighted average debt maturity calculated according to Equation (1). Event time 0 denotes the portfolio formation year. Event time s denotes the s^{th} year subsequent to the portfolio formation year and event time -s denotes the s^{th} year prior to the portfolio formation year. The solid curves represent the portfolio's average debt maturity and the long-dashed curves surrounded represent the 95% confidence interval. Debt maturity evolution is displayed for all firms in Panel A and for survivors in Panel B. Survivors are defined as firms who have more than 20 debt maturity observations. The portfolio formation procedure is described as below. Each year, we sort firms by debt maturity levels and split them into four equal groups. Then for each portfolio constructed in a given year, we calculate the average debt maturity for firms present in the portfolio for the subsequent 20 years. The portfolio composition remains relatively unchanged unless a firm spontaneously perishes and exits the portfolio. For each year from 1974 to 2010, we repeat the above sorting and averaging procedure, which generates 37 sets of event-time averages for each portfolio. We next plot the mean of the event-time averages and the two-standard error interval of the average debt maturity across event time. The sample consists of 6458 U.S. listed & based non-financial non-utility firms in the CRSP/Compustat Merged database over the period 1974-2011.

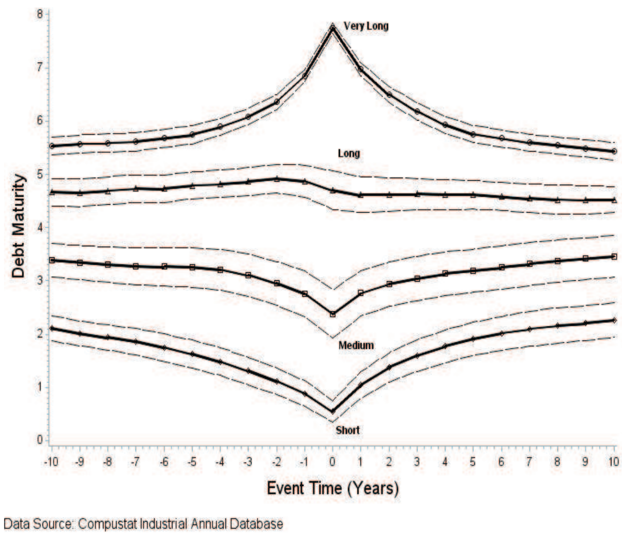
Panel A: Forward-looking
(All Firms)



Panel B: Forward-looking
(Survivors)



Panel C: Forward- and Backward-looking
(All Firms)



Panel D: Forward- and Backward-looking
(Survivors)

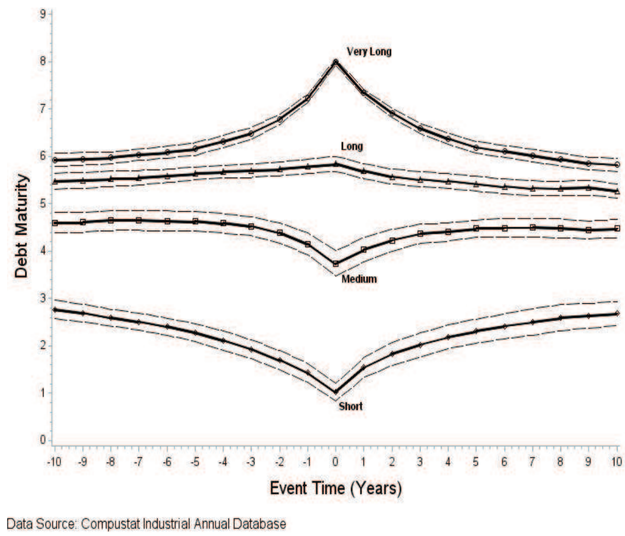
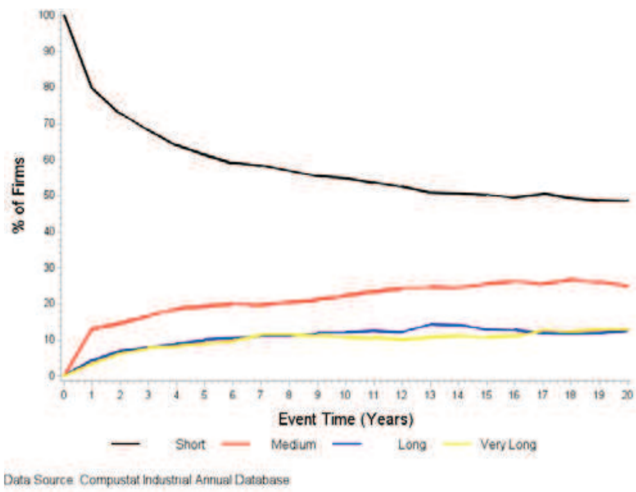


Figure II

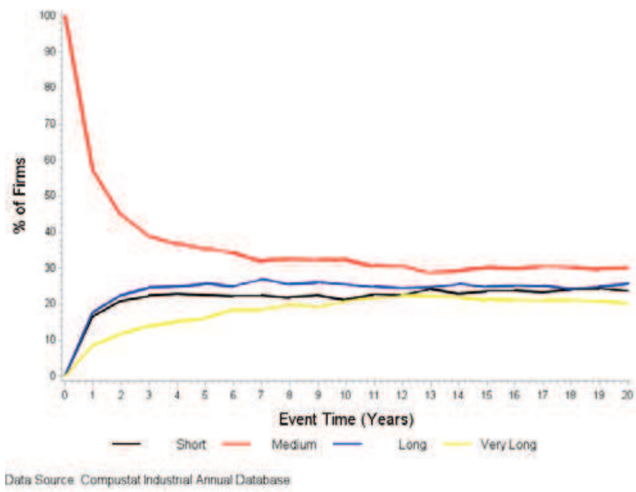
The Distribution of Survivor Firms throughout Debt Maturity Portfolios in Event Time

This table exhibits the distribution of survivor firms in percentage throughout debt maturity portfolios in event time for initially short (Panel A), medium (Panel B), long (Panel C) and very long (Panel D) debt maturity portfolios. Debt maturity is calculated according to Equation (1). We focus on a group of firms who have complete debt maturity information for the entire 20-year event time period. The portfolios are constructed based on firms' weighted average debt maturity. Event time 0 denotes the portfolio formation year and event time s denotes the s^{th} year subsequent to the portfolio formation year. The curves represent the percentage of firms that remain in a specific debt maturity portfolio. Below is the portfolio formation procedure. Each year, we sort firms by debt maturity levels and split them into four equal groups. Then for each portfolio that is constructed in a given year, we calculate the percentage of firms who are present in a specific portfolio for the subsequent 20 years. The portfolio composition remains strictly unchanged. For each year from 1974 to 1991, we repeat the above sorting and averaging procedure, which generates 18 sets of event-time percentages for each portfolio. We next plot the mean of the event-time percentages across event time. The sample consists of 1083 U.S. listed & based non-financial non-utility firms in the CRSP/Compustat Merged database.

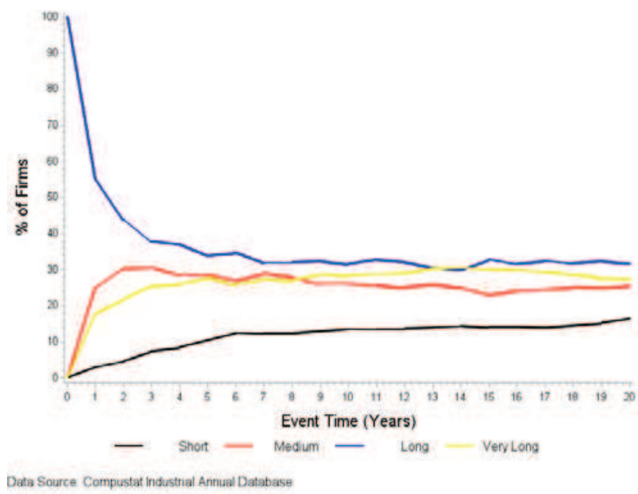
Panel A: Initially Short Debt Maturity Portfolio



Panel B: Initially Medium Debt Maturity



Panel C: Initially Long Debt Maturity Portfolio



Panel D: Initially Very Long Debt Maturity Portfolio

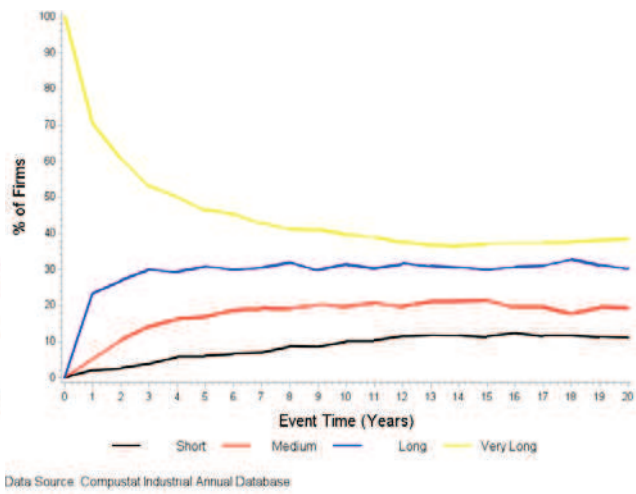
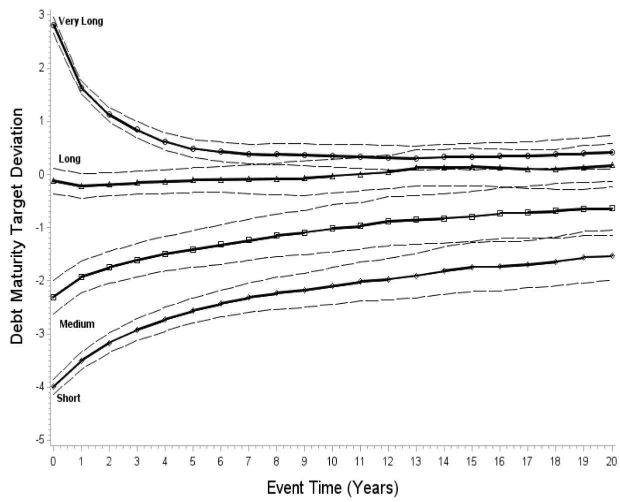


Figure III

Average Debt Maturity Target Deviation of Actual Debt Maturity Portfolios in Event Time

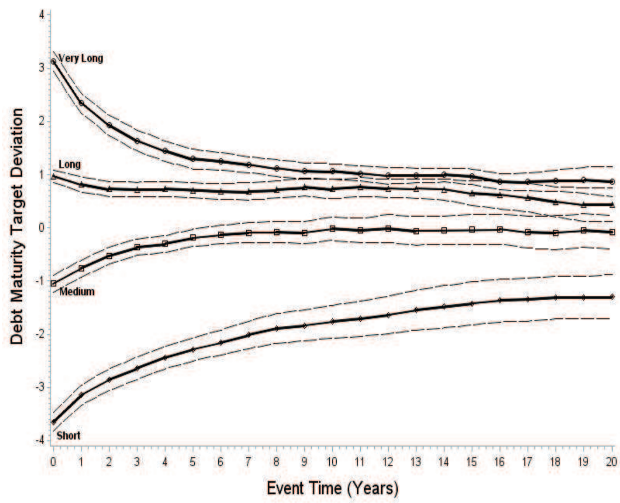
This figure exhibits average debt maturity target deviation in event time for four portfolios constructed based on firms' weighted average debt maturity. Event time 0 denotes the portfolio formation year. Event time s denotes the s[th] year subsequent to the portfolio formation year and event time -s denotes the s[th] year prior to the portfolio formation year. Debt Maturity is calculated according to Equation (1). Debt Maturity target deviation is defined as the difference between the observed and the target debt maturity. In Panel A and Panel B, debt maturity target is defined as the weighted average debt maturity of peer firms in the same industry as the firm under observation, with each firm weighted by its total liabilities. In Panel C and Panel D, debt maturity target is estimated as the fitted value from the OLS regression based on firm's historical panel information, specified as in the following model, $DMAT_{i,t} = \alpha_\theta + \beta_{1\theta} Size_{i,t-1} + \beta_{2\theta} Leverage_{i,t-1} + \beta_{3\theta} Asset\ Maturity_{i,t-1} + \beta_{4\theta}\ Market - to - Book_{i,t-1} + \beta_{5\theta} R\&D_{i,t-1} + \gamma_\theta Industry_i + \varepsilon_{i,t} \quad i = 1, \dots, n \ t = 1, \dots, T$. The target debt maturity for the firm i in year t is computed by applying the coefficient estimates to firm i's characteristics measured as of year t-1. In Panel E and Panel F, debt maturity target is estimated as the fitted value from the 25[th], 50[th] and 75[th] quantile regressions based on firm's historical panel information, specified as in the following model, $\left(DMAT_{i,t} \middle| X_{i,t-1}\right) = \alpha_\theta + \beta_{1\theta} Size_{i,t-1} + \beta_{2\theta} Leverage_{i,t-1} + \beta_{3\theta} Asset\ Maturity_{i,t-1} + \beta_{4\theta} Market - to - Book_{i,t-1} + \beta_{5\theta} R\&D_{i,t-1} + \gamma_{i\theta} Industry_i + \varepsilon_{i,t} \quad i = 1, \dots, n \ t = 1, \dots, T$. The target debt maturity for the firm i in year t is computed by applying the coefficient estimates of the corresponding debt maturity quantile to firm i's characteristics measured as of year t-1. That is, the 25th quantile regression results apply to $DMAT_{t-1}$ inferior to the 0.25 percentile, the 50th quantile regression results apply to $DMAT_{t-1}$ superior to the 0.25 percentile and inferior to the 0.75 percentile, and the 75th quantile regression results apply to $DMAT_{t-1}$ superior to the 0.75 percentile. . In Panel G and Panel H, debt maturity target is defined as the time-series average of a firm's historical debt maturities. The solid curves represent the portfolio's average debt maturity target deviation and the long-dashed curves surrounded represent the 95% confidence interval. The evolution pattern is displayed for all firms (Panel A, Panel C, Panel E and Panel G) and survivors (Panel B, Panel D, Panel F and Panel H). Survivors are defined as firms who have more than 20 debt maturity observations. The portfolio formation procedure is described as below. Each year, we sort firms by debt maturity levels and split them into four equal groups. Then for each portfolio constructed in a given year, we calculate the average debt maturity target deviation for firms present in the portfolio for the subsequent 20 years. The portfolio composition remains relatively unchanged unless a firm spontaneously perishes and exits the portfolio. For each year from 1974 to 2010, we repeat the above sorting and averaging procedure, which generates 37 sets of event-time averages for each portfolio. We next plot the mean of the event-time averages and the two-standard error interval of the average debt maturity target deviation across event time. The sample consists of 6458 U.S. listed & based non-financial non-utility firms in the CRSP/Compustat Merged database over the period 1974-2011.

Panel A: Peer Firms' Weighted Average Debt Maturity as Target Proxy (All Firms)



Data Source: Compustat Industrial Annual Database

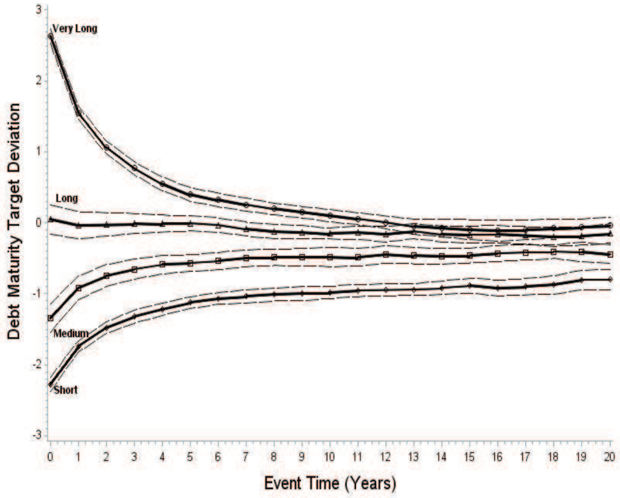
Panel B: Peer Firms' Weighted Average Debt Maturity as Target Proxy (Survivors)



Data Source: Compustat Industrial Annual Database

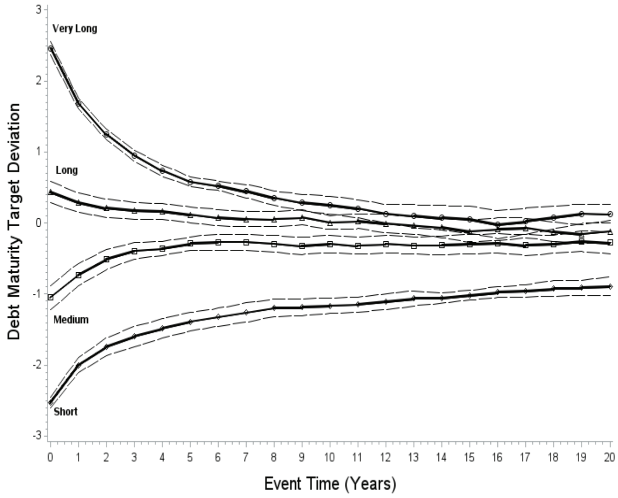
Figure III (Continued)

Panel C: OLS Regression Predicted Debt Maturity as Target Proxy (All Firms)



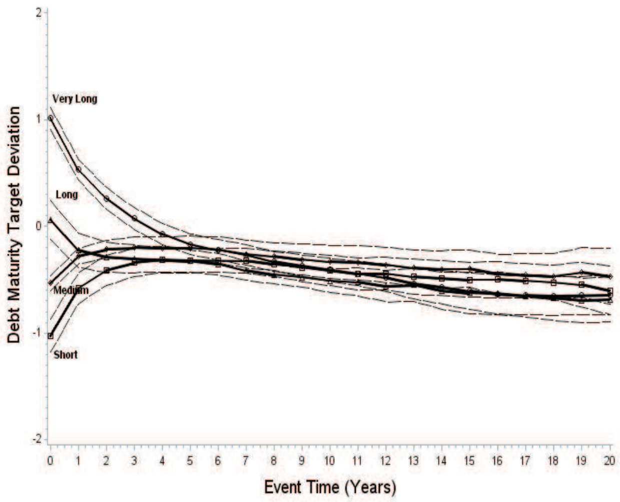
Data Source: Compustat Industrial Annual Database

Panel D: OLS Regression Predicted Debt Maturity as Target Proxy (Survivors)



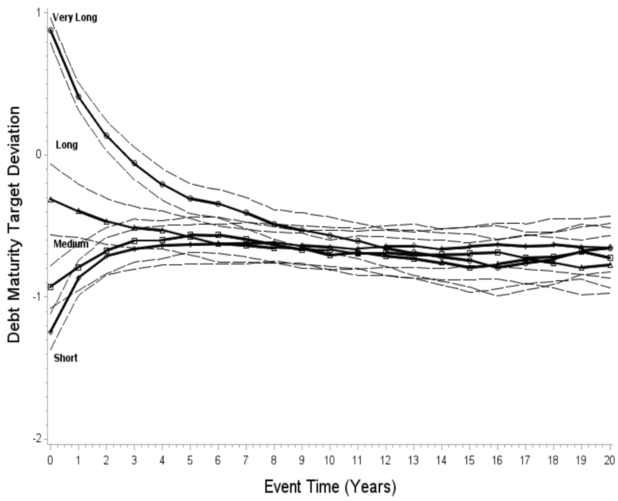
Data Source: Compustat Industrial Annual Database

Panel E: Quantile Regression Predicted Debt Maturity as Target Proxy (All Firms)



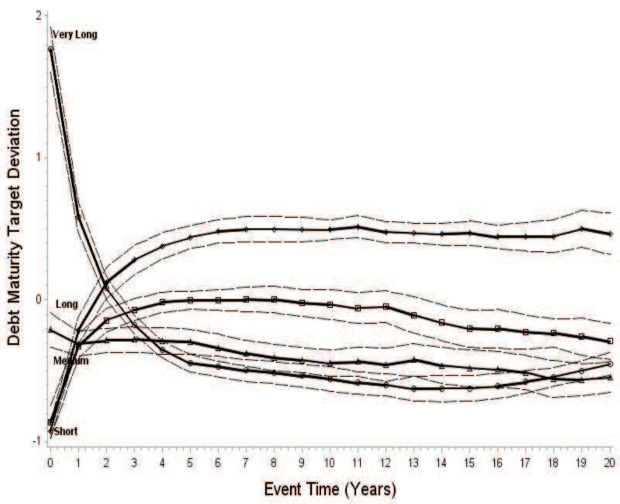
Data Source: Compustat Industrial Annual Database

Panel F: Quantile Regression Predicted Debt Maturity as Target Proxy (Survivors)



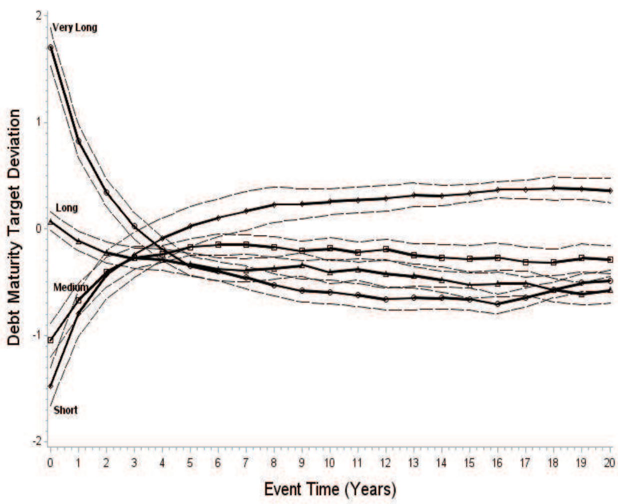
Data Source: Compustat Industrial Annual Database

Panel G: Firm's Past Debt Maturity Average as Target Proxy (All Firms)



Data Source: Compustat Industrial Annual Database

Panel H: Firm's Past Debt Maturity Average as Target Proxy (Survivors)



Data Source: Compustat Industrial Annual Database